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Rainfall-runoff modeling using artificial neural networks in the Mono River basin (Benin, West Africa)

Biao Iboukoun Eliezer
Assistant Professor, National School of Mathematical Engineering and Modeling, National University of Sciences, Technology, Engineering and Mathematics, Abomey, Benin
Obada Ezechiel
Assistant Professor, National School of Public Works, National University of Sciences Technology, Engineering and Mathematics, Abomey, Benin
Moussa Djibril Aliou
Segbede Armand
Assistant Professor, National School of Mathematical Engineering and Modeling, National University of Sciences, Technology, Engineering and Mathematics, Abomey, Benin
Alamou Adechina Eric
Full Professor, National School of Public Works, National University of Sciences Technology, Engineering and Mathematics, Abomey, Benin

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Abstract

Hydrological models are developed to simulate river flows over a watershed for many practical applications in the field of water resource management. However, the rainfall-runoff models mostly used in the Mono river basin struggle to better simulate high river flows. This paper presents a modeling approach based on Artificial Neural Networks (ANN) under different input meteorological parameters in the Mono River basin to better take into account the non-linearity of the relationship between rainfall and runoff. To this end, precipitation, potential evapotranspiration, and previously observed flow have been used for the daily flow simulation. The Levenberg-

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Marquardt algorithm is used to train the ANN rainfall-runoff models over the other optimization training algorithms mostly implemented in the study area. The analysis of the rainfall-runoff variability allowed us to show the strong correlation between rainfall and runoff and the impact of the Nangbéto dam on the flows at Athiémé. The results obtained after the training, validation, and testing of the ANN models are satisfactory (e.g., the coefficient of correlation varies between 0.93 and 0.99). The most efficient model has been identified and implemented in the Mono river basin at Nangbéto. The satisfactory results obtained show that ANN models can be considered good alternatives for traditional rainfall-runoff modeling approaches.

Keywords: Mono river basin, variability, modeling, artificial neural networks, Levenberg-Marquardt algorithm, non-linearity

Introduction

Rainfall is generally the greatest contribution to the water balance of a river basin. The transformation of rainfall into flow is a phenomenon of great importance which, for several years, has been the subject of numerous studies. Indeed, the rainfall-runoff relationship is one of the most complex hydrologic phenomena to comprehend due to the tremendous spatial and temporal variability of the river basin characteristics and precipitation patterns, as well as the number of variables involved in modeling of physical processes (Joshi and Patel, 2011).

Several studies used artificial neural networks (ANN) for modelling complex hydrological processes, such as rainfall-runoff (Hsu and Gupta, 1995; Lorrai and Sechi, 1995; Minns and Hall, 1996; Dawson and Wilby, 1998; Tokar and Johnson, 1999; Rajurkar et al., 2002; Wilby et al., 2003; Giustolisi and Laucelli, 2005; Jain and Srinivasulu, 2006). Relatively few studies have tested the practicability of using ANN with various input configurations to model the rainfall-runoff relationship. For example, the river flow does not only depend on total rainfall, but also on other meteorological parameters. Thus, a simple adjustment to ANN input data can be made to ameliorate their performance in flow simulation. Researches also showed that ANN are one of the most promising tools in hydrology (ASCE Task Committee, 2000a; 2000b; Maier and Dandy, 2000; Dawson and Wilby, 2001). ANN can map the underlying relationship between input and output data without a prior understanding of the process under investigation (Kalteh, 2008). However, according to Kalteh (2008), ANN have been mostly criticized for their black-box nature due to the fact that the primary application of an ANN is the nonlinear modeling of input-output observations in order to obtain accurate modeling of the system’s response. Nevertheless, several authors such as (Chergui, 2019; Lek et al., 1996; Kharroubi et al., 2016; Yao

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et al., 2014) showed that these models, inspired by the functioning of biological neurons, are very efficient for simulating and predicting river flows in catchment areas. Zohou et al. (2023) used two ANN models such as the Long Short-Term Memory (LSTM) and Recurrent Gate Networks (GRU) in the Oueme River basin at Savè outlet in Bénin. They found a strong similarity between the observed and simulated flows. Their results demonstrate the effectiveness of artificial intelligence-based models in hydrological modeling. Mohseni and Muskula (2023) examined the rainfall-runoff-based model development using ANN models in the Yerli sub-catchment of the Upper Tapi basin in India. These authors used the Levenberg-Marquardt, Bayesian Regularization and Conjugate Gradient Scaled algorithms to train the ANN rainfall-runoff models. Their results show that Levenberg-Marquardt creates the most accurate model.

In the Mono River basin, the non-linearity of the rainfall-runoff relationship accentuated by the presence of the Nangbéto dam, limits hydrological modeling by conventional methods. To date, relatively few studies have used ANN rainfall-runoff models in the study area and a clear picture of its performance is lacking. In order to fill this gap, the present study examines the rainfall-runoff modeling development by using ANN models under different input meteorological parameters in the Mono River basin at Athiémé. The Levenberg-Marquardt algorithm is used to train the ANN rainfall-runoff models over the other optimization training algorithms mostly implemented in the study region. The performance of the most efficient model is then tested at Nangbéto outlet of the investigated river basin.

Materials and methods

Study area and data used

The Mono River basin at Athiémé occupies an area of 21,500 km² shared between two West-African countries, Togo and Benin. Specifically, it is located between the latitudes 06o16’N and 09o20’N, and the longitudes 0o42’E and 2o25’E (Figure 1). It hosts the Nangbéto hydropower dam, which was built in 1987 and utilized by the two countries. The river serves as a natural border between the two countries in the southern part. The climate is tropical (two rainy seasons and two dry seasons) downstream and subequatorial (one rainy season and one dry season) upstream (Lawin et al., 2019). This river basin is patterned in the south by floodplains and plateaus, and higher landforms in the north and north-west, e.g., the Atakora Mountains with a height of 800 m and their southern extensions are the Togo mountains (Amoussou et al., 2020). Its water storage capacity is 1,715 Mm3 (Amoussou, 2010).

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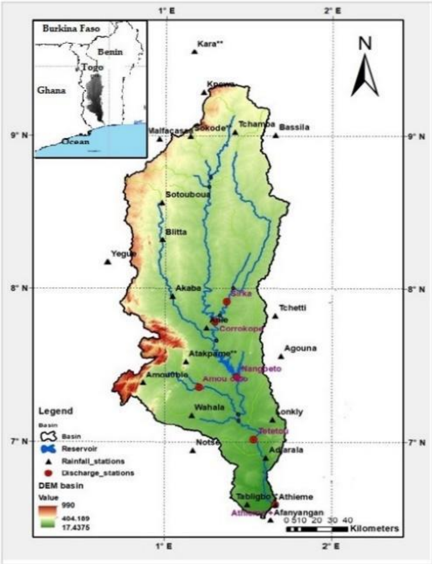

Figure 1: Study area

Observed meteorological data (daily rainfall data, potential evapotranspiration data estimated by the Penman-Monteith formula) and daily river discharge data were provided respectively, by the Benin and Togo Meteorological Department and the National Directorate of Water (DG-Eau) of Benin. The observed data are considered for the period 1961–2010 (good compromise, taking into account the length of the available data in the different stations). Average rainfall over the basin is obtained by the ordinary kriging method applied to 17 rainfall stations.

Methods

Rainfall-runoff interannual variability

The rainfall and runoff anomaly indices are calculated using Eq (1) for the analysis of the interannual variability of these variables.

$$\varepsilon_{i} = \frac{\boldsymbol{X_i - \underline{X}}}{\boldsymbol{\sigma_X}} \tag{1}$$

where $\boldsymbol{X_i}$ is the annual value of rainfall/runoff in year $\boldsymbol{i}$; $\underline{\boldsymbol{X}}$ is the average value of $\boldsymbol{X_i}$ over the period 1961–2010 and $\boldsymbol{\sigma_X}$ its standard deviation.

Data preprocessing

Before loading the data into the ANN rainfall-runoff models, a few transformations were applied, such as data normalization and transforming time series into supervised learning series. Normalization and standardization

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are common techniques not limited to time series. Especially when working with algorithms that are sensitive to the range of input values (e.g. neural networks), this preprocessing step plays an important role. The simplest way to transform a time series forecast into a supervised learning problem is by creating lag features. The first approach is to predict the value of time $\boldsymbol{t}$ given the value at the previous time $\boldsymbol{t-1}$. A key function to help transform time series data into a supervised learning problem is the Pandas shift() function. Given a DataFrame, the shift() function can be used to create copies of columns that are pushed forward (rows of NaN values added to the front) or pulled back (rows of NaN values added to the end). This is the behavior required to create columns of lag observations, as well as columns of forecast observations for a time series dataset in a supervised learning format.

Normalization

Precipitation and evapotranspiration data will be normalized in [0, 1] according to the relationship:

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

where x and y stand respectively for the initial and normalized data vectors. x_{max} *and* x_{min} are respectively the maximum and minimum values of the initial data. For the flow data, a logarithmic transformation is applied.

Split the Dataset

Our hydrometeorological data is divided into three main parts to ensure the training, validation, and testing of the ANN models (Table 1). It has been noticed a lot of missing data in the observed data. Thus, consecutive years without gaps have been identified and the period 1971-1977 is used for supervised learning.

- A first data set is used to train the models. This set covers 60% of the dataset (01-01-1971 to 11-03-1975). This data set allows learning the different weights of the neurons constituting our network.
- A second data set is used to validate the model parameters (validation set). This set represents 20% of the dataset (12-03-1975 to 05-08-1976). This data sample provides an unbiased evaluation of the model fit on the training data set while adjusting the models hyperparameters.
- A third data set is used to test the real performance of the models. This dataset also represents 20% of the dataset (06-08-1976 to 31-12-1977). This is the test sample and it is used only after the model is fully trained (using the training and validation sets). This step allows to provide an unbiased assessment of the fit of the final model on the training dataset.

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Table 1: Dataset split

Phase	Percentage	Period
Training set	60%	1971 - 1977
Validation set	20%	
Test set	20%	

Artificial Neural Networks model

The model of neural networks used in this study is the multi-layer perceptron (MLP). An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer (Figure 2). Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a chain rule based supervised learning technique called backpropagation or reverse mode of automatic differentiation for training.

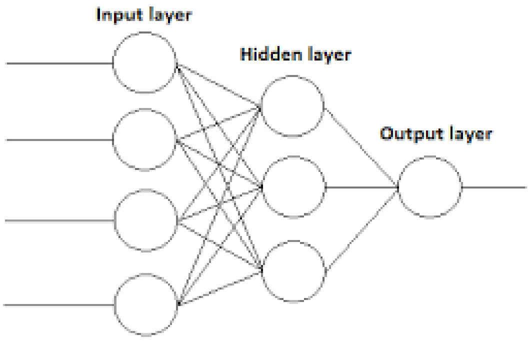

Figure 2: Multi-layer Perceptron

When the signals X_i, are presented to the input of the neuron, the information processing module performs their weighted addition, denoted by v_k, such as:

$$v_k = \sum_{j=1}^{n} w_{kj} X_j \tag{3}$$

where w_{kj} stands for the weight from neuron j to neuron k.

Then a transfer function ϕ is applied to the resulting signals, while adding to its an external quantity called the activation threshold b_k. A value representative of all the signals (y_k) is then obtained at the output of the neuron such that

$$y_k = \phi(v_k + b_k) \tag{4}$$

The transfer function ϕ can be linear or non-linear. In the present study, the transfer function ϕ used for the hidden layer is the hyperbolic tangent function (due to its main properties such as: non-linearity, smoothness, output range between -1 and 1, etc..) given by Eq (5)

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$$\phi(v) = tanh\,(v) = \frac{1}{1 - e^{-2v}} - 1 \quad (5)$$

whereas the one used for the output layer is the identity function (purelin)

$$\phi(v) = v \quad (6)$$

Levenberg-Marquardt algorithm

The principle of this algorithm is based on an iterative method of adjusting the free parameters of a Multilayer Perceptron network (Marquard, 1963). It uses the principle of minimizing an error cost function. The free parameters of the network are adjusted at each iteration according to the value of the error taken at the output of the network.

Assuming that $\hat{y}$ is the output of the network:

$$\hat{y} = \alpha_0 + \sum_{k=1}^{p} \alpha_k tanh(v_k + b_k) \quad (7)$$

where p is the number of neurons of the hidden layer; α_k is the weight linking the neuron k of the hidden layer to the neuron of the output layer.

The associated error is given at each iteration by $e = y - \hat{y}$ (Eq. 8)

$$e = y - \left[\alpha_0 + \sum_{k=1}^{p} \alpha_k tanh(v_k + b_k)\right] \quad (8)$$

The cost function that the Levenberg-Marquardt algorithm seeks to minimize while adjusting the network parameters is the squared error related to Eq (8). This algorithm uses the Gauss-Newton method to determine the optimal parameters of the network.

River flow simulation

We used the neural network fitting and neural network time series modules in MATLAB. For the simulation of the river flow, three types of models of neural network are investigated. The first ANN model considers a combination of precipitation, potential evapotranspiration on day t and observed flow values on day $t-1$ as input variables for the flow simulation on day t. These variables are mostly the inputs of hydrological models.

- ***Model 1***

$$Q(t) = f_1\big(P(t), \quad ETP(t), \quad Q(t-1)\big) \quad (9)$$

where

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$$f_1 = \alpha_0 + \sum_{j=1}^{p} \alpha_k tanh(v_k + b_k) \text{ and } v_k = w_{k1}P(t) + w_{k2}ETP(t) + w_{k3}Q(t-1)$$

In Eq (9), $P(t),\ ETP(t)\ and\ Q(t-1)$ stand respectively for precipitation, potential evapotranspiration on day t, and the river flow on day $t-1$.
The second ANN model considers only previously observed precipitations as input variables for the daily flow simulation.

- ***Model 2***

$$Q(t) = f_2\big(P(t-1), \quad P(t-2), \dots, \ P(t-r)\big) \tag{10}$$

By taking into account the expression of f_2, Eq (10) can be written in the form

$$Q(t) = \alpha_0 + \sum_{k=1}^{p} \alpha_k tanh\big(w_{k0} + w_{k1}P(t-1) + \cdots + w_{kr}P(t-r)\big) \tag{11}$$

The third ANN model considers a combination of previously observed precipitation, potential evapotranspiration and flow values as input variables for the daily flow simulation.

- ***Model 3***

$$Q(t) = f_3\big(P(t-1),\ ETP(t-1),\ Q(t-1)\big) \tag{12}$$

which can be written in the form

$$Q(t) = \alpha_0 + \sum_{k=1}^{p} \alpha_k tanh\big(w_{k0} + w_{k1}P(t-1) + w_{k2}ETP(t-1) + w_{k3}Q(t-1)\big) \tag{13}$$

Table 2 shows the different parameters used to configure the networks.

Table 2: Parameters of ANN models used

Parameters	Choice
Type of network	Feed-forward back propagation
Structure of the developed network	Multi-layers Perceptron (Feed-Forward)
Input	Parameters of the function f according to the model (P, ETP, previous river flow Q)
Output	River flow (Q)
Learning algorithm	Levenberg-Marquardt
Performance functions	Mean Squared Error (MSE), coefficient of correlation (R) and Nash coefficiency
Number of layers	2
First layer activation function (hidden layer)	Tangential sigmoid
Second layer activation function (output layer)	Linear (PURELIN)

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The Nash–Sutcliffe model efficiency coefficient can be given in the form:

$$Nash = 1 - \frac{\sum_{t=1}^{T} (Q_0^t - Q_s^t)^2}{\sum_{t=1}^{T} \left(Q_0^t - \underline{Q}_0\right)^2} \tag{14}$$

where $\underline{Q}_0$ is the mean observed river flow, Q_s^t is the simulated river flow and Q_0^t is the observed river flow at time t.

Then, the most efficient models are tested in the Mono River basin at Nangbéto outlet in order to judge their capability to provide a good simulation in another river sub-basin of the study area.

Results and Discussion

Distribution of daily river flow

The study period is divided into two part: 1961 – 1987 (period before the establishment of the Nangbéto dam) and 1988 – 2010 (period after the establishment of the dam in 1987). This subdivision was done to consider the effect of the dam's operation on the flow at Athiémé outlet. Figure 3 shows that the distribution of daily flows presents a high variability from 1988-2010 compared to the period preceding the impoundment of the dam. There is an increase of about 37% in the average annual flow afler the dam's impoundment compared to the previous one. Indeed, Nangbéto dam has a strong influence on the flows at Athiémé outlet, and this confirms the artificial nature of the Mono's hydrological regime since the establishment of the Nangbéto dam. These results align with the works of Amoussou (2010) and Biao et al. (2021).

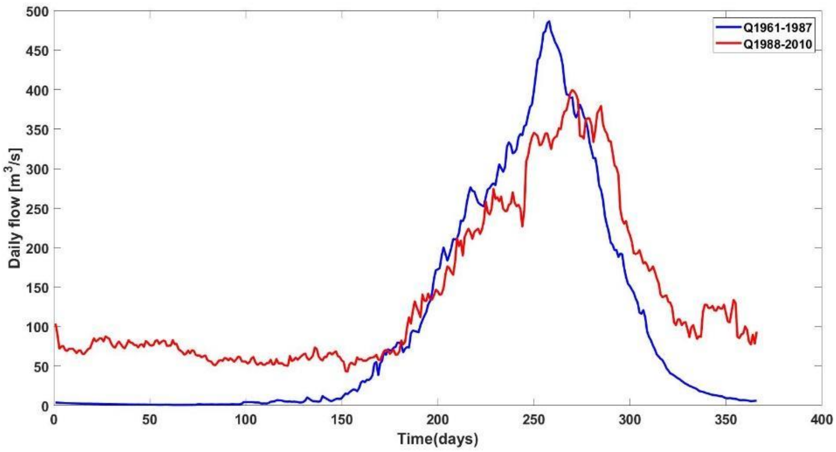

Figure 3: Distribution of daily river flows at Athiémé outlet

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Rainfall-runoff interannual variability

Figure 4 shows a drop in rainfall over the last two decades of the study period compared to the 1960s. However, this drop is less pronounced than that of the period 1970-1975. It is almost the same pattern for runoff. This justifies the correlation between rainfall and runoff. The two extremes (i.e. wet year in 1963 and dry year in 1983) coincide for both rainfall and flow.

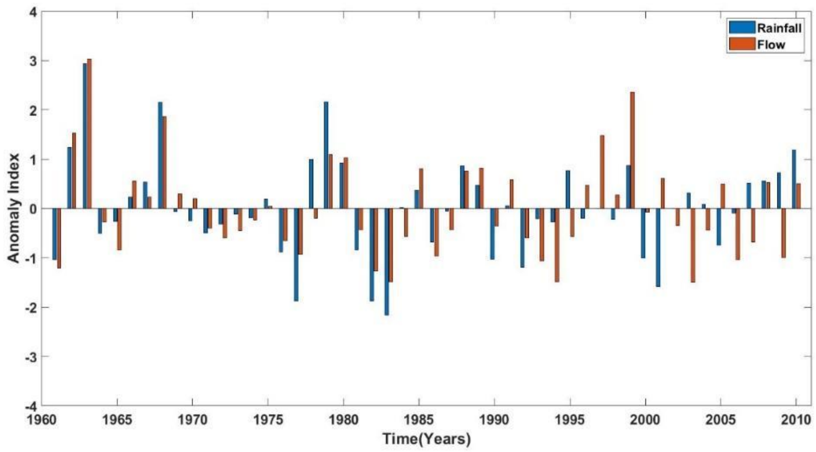

Figure 4: Rainfall-runoff interannual variability

Supervised learning

Supervised learning is performed over the period 1971-1977 because it represents the longest series of consecutive years without gaps.

Neural network fitting

Figure 5 shows the network configured for Model 1. One can see that the input of the network is three (3), which represents the three (3) input parameters of the model (i.e. $P(t),\ ETP(t),\ Q(t-1)$) and at the output we have the flow at day t. In the hidden layer we notice 10 neurons, whereas in the output layer only one neuron is seen because we have one output (i.e. flow). The vector of weights W and that of the biases b, as well as the transfer functions are indicated on the network.

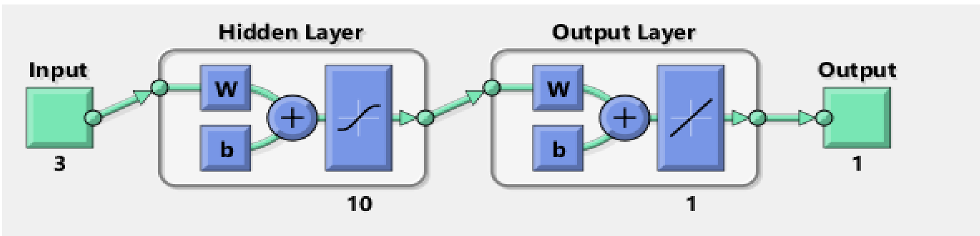

Figure 5: Network configured for Model 1

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Results of supervised learning, after 12 iterations, are summarized in Figure 6:

Results

	Samples	MSE	R
Training:	1533	3.71042e-2	9.96424e-1
Validation:	511	3.39696e-2	9.96835e-1
Testing:	511	6.41221e-2	9.93044e-1

Figure 6: Supervised learning results using Model 1

Neural network time series

Figure 7 shows the network configured for Model 2. Once the data is entered, the network is created with 10 neurons with the specificity of the delay number r (r = 100) as shown in Figure 7. At the input we have precipitations and at the output, the flow.

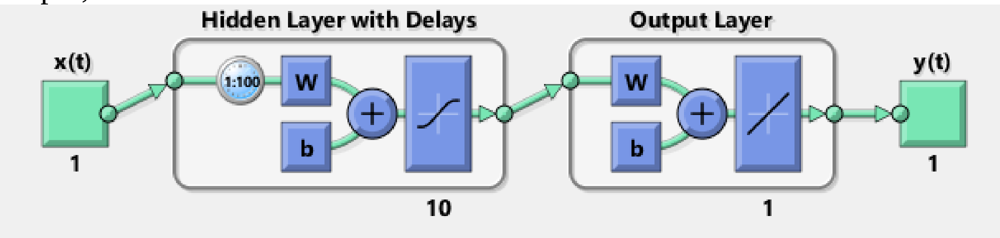

Figure 7: Network configured for Model 2

Results of the supervised learning, after 23 iterations, are given in Figure 8:

Results

	Target Values	MSE	R
Training:	1533	6.88162e-1	9.30525e-1
Validation:	511	9.62730e-1	9.03944e-1
Testing:	511	9.70365e-1	9.06945e-1

Figure 8: Supervised learning results using Model 2

Figure 9 shows the network configured for Model 3. We can see that the input of the network is three (3), which represents the three (3) input parameters of the model $(P(t-1),\ ETP(t-1),\ Q(t-1))$ and at the output we have the flow. x(t) at the input is composed of the first two (2) parameters, while the y(t) is the third model parameter. The number of delays r is 1. In the hidden layer we have 10 neurons and one neuron at the output layer. The vector of

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weights W and that of the biases b as well as the transfer functions are indicated on the network.

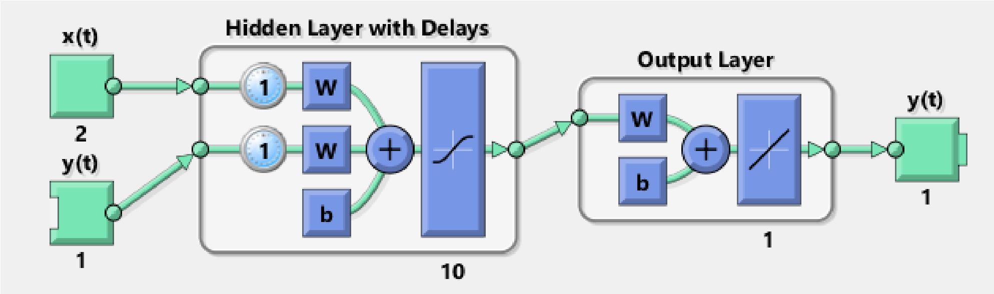

Figure 9: Network configured for Model 3

Results of the supervised learning, after 27 iterations, are summarized in Figure 10:

Results

	Target Values	MSE	R
Training:	1533	3.97633e-2	9.96182e-1
Validation:	511	4.58328e-2	9.95357e-1
Testing:	511	3.78191e-2	9.96055e-1

Figure 10: Supervised learning results using Model 3

Table 3 summarized the performance of the three models.

Table 3 : Performance of the models

Models	Training		Validation		Testing	
	R	MSE	R	MSE	R	MSE
Model 1	**0.99**	**0.037**	**0.99**	**0.034**	**0.99**	**0.064**
Model 2	0.93	0.688	0.90	0.962	0.91	0.970
Model 3	**0.97**	**0.039**	**0.95**	**0.045**	**0.96**	**0.037**

The results of Table 3 allow us to conclude that the three investigated models performed well in training, validation and testing, which are justified by the values of R close to 1 and those of the MSE is low because the error order is between 10^{-1} and 10^{-2}, especially for Models 1 and 3. Indeed, Models 1 and 3 performed better than Model 2. This can be justified by adding a second meteorological parameter (i.e. evapotranspiration) as input to the ANN model. These findings have also been highlighted by Aoulmi et al. (2020) who tested the practicability of ANN models with different input configuration in Seybouse basin (Northeast Algeria). They found that as much input variables are numerous, as more the model of ANN is efficient.

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Simulation of Mono river flow at Athiémé

Precipitation and potential evapotranspiration data for the time-period 1961-1964, which have not been taken into account for supervised learning, were now used to simulate the river flow. Figures 11, 12 and 13 show the flows simulation respectively from Models 1, 2 and 3. It can be seen from these figures that Model 1 better reproduce the observed hydrograph compared to Models 2 and 3. The values of the performance criteria MSE, R and Nash used in this study are given in Table 4. The values of the criteria MSE, R and Nash confirm the excellent quality of model 1 over Models 2 and 3.

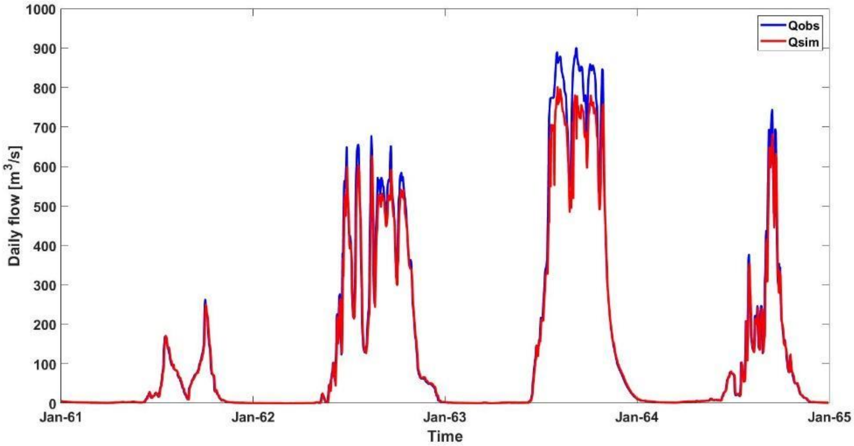

Figure 11: Observed and simulated flows in Mono River basin at Athiémé for the time-period 1961-1964 using Model 1

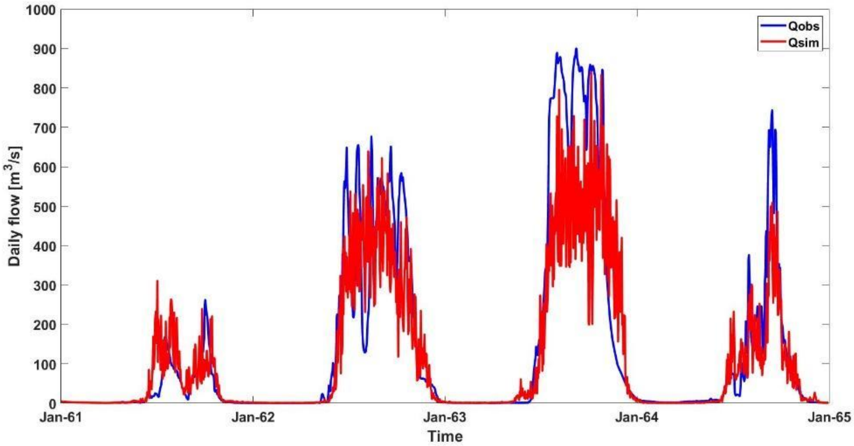

Figure 12: Observed and simulated flows in Mono River basin at Athiémé for the time-period 1961-1964 using Model 2

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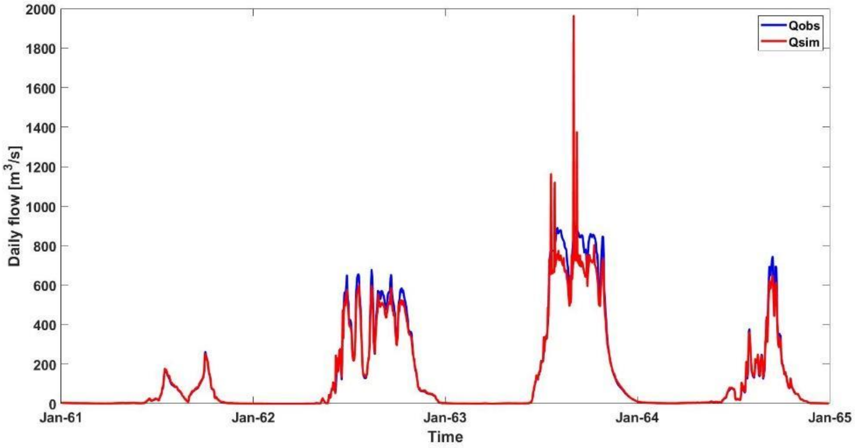

Figure 13: Observed and simulated flows in Mono River basin at Athiémé for the time-period 1961-1964 using Model 3

Table 4: Models performance (ranged by decreasing performance)

Models	MSE	R	Nash	Quality
Model1	0.0270	0.99	99.61%	Excellent
Model3	0.0282	0.97	96.61%	Excellent
Model2	0.9885	0.93	86.23%	Good

The works carried out by Biao et al. (2021) on the hydrological modeling of the Mono basin at Athiémé showed that with the use of HBV (Seibert, 2005), ModHyPMA (Afouda and Alamou, 2010), GR4J (Perrin et al., 2007), AWBM (Boughton, 2004) hydrological models and a combination of these four models, the values of the Nash criterion varie between 36% and 81%. In addition, the works of Koubodana et al. (2021), which used GR4J and IHACRES (Jakeman and Hornberger, 1993) hydrological models, gave values of the Nash criterion between 60% and 90%. Thus, one can conclude that the performances of the investigated ANN models in this research are better than those found in previous works in the study area. The ANN models used in this study better simulate high river flows compared to the hydrological models mostly used the study area. However, the uncertainties that are still associated with the peaks can be explained as a result of increasing soil moisture, rather than isolated rain spells in the basin. Based on the power and capacity to simulate reasonably correct flows, ANN models can be considered good alternatives for traditional rainfall-runoff modeling approaches.

Testing the most efficient models at Nangbéto outlet

The most efficient model in simulating flow in Mono River basin at Athiémé (i.e. Model 1) tested with data from the Mono River basin at Nangbéto outlet responds also well and gives a Nash criterion of 80% (Figure 14). The results obtained by Amoussou et al. (2014) in this aforementioned basin using GR4J hydrological model gave a value of the Nash criterion of about 78% over the period 1996-2003 and 62% over the period 2004-2010. We can therefore realize the generalization capacity of the ANN models. The good capability of ANN to model hydrological process has also been highlighted by previous studied. For instance, Riad et al. (2004) showed that ANN are useful and powerful tools for handling complex problems compared to traditional models. Kumar et al. (2016) concluded that the simulated daily runoff using ANN model fairly matched with the observed values. The findings of this present study clearly show that the artificial neural networks can better model rainfall-runoff relationship.

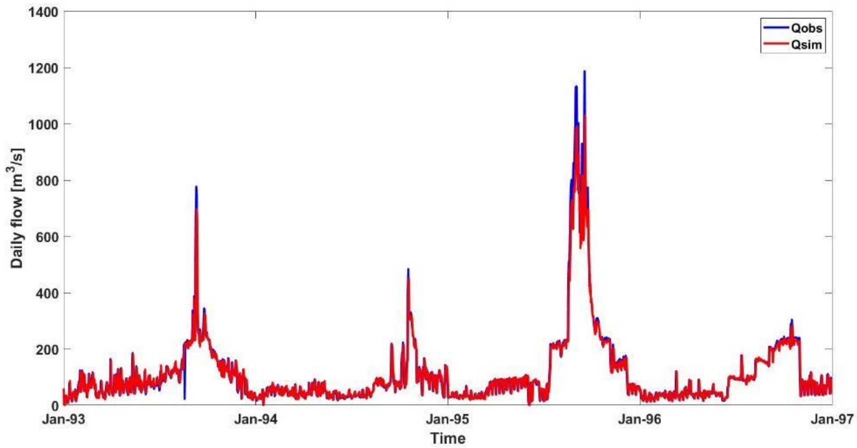

Figure 14: Observed and simulated flows in Mono River basin at Nangbéto for the time-period 1993-1996 using Model 1

Conclusions

The main contribution of this paper is to investigate ANN rainfall-runoff models under different input meteorological parameters for a better understanding of the hydrological behavior of the Mono River basin. The study of the rainfall-runoff variability showed a strong correlation between rainfall and runoff and highlights the main role played by the Nangbéto dam in the non-linearity of the rainfall-runoff relationship at the Athiémé outlet. Using ANN models under different input meteorological parameters with the Levenberg-Marquardt algorithm allowed us to simulate river flow and gave good performances (Nash criterion varies between 86% and 99%). The investigated models were very efficient and gave simulated flows almost identical to the observed flows. However, as much input variables are numerous, as more the model of ANN is efficient. The implementation of the most efficient model (i.e. Model 1) in the Mono River basin at Nangbéto outlet

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yielded also to good results and confirms, therefore, the generalization capacity of ANN. The ANN approach is a promising tool to solve problems in water resources and management.

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