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Rain-Flow Modeling Using a Multi-Layer Artificial Neural Network on the Watershed of the Cavally River (Côte d'Ivoire)

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Abstract

Water resources management is nowadays a significant stake for the world. However, missing or bad quality of the hydro-climatic historical data available of the studied area makes sometimes hydrological studies difficult. Generally, conceptual rain-flow models are designed to bring an appropriate answer with the correction of gaps and prediction of the flows. Historical hydro-climatic data of the Ity station, located on Cavally River, contain gaps which must be bridged. This study aims to establish a rainfall-runoff model through artificial neural networks for filling the gaps into the flow data series of the hydrometric station of Ity on the watershed of Cavally River. A multi-layer perceptron of feed forwards with two entries (monthly average rain and evapotranspiration) and an exit (flows) was established with flow evapotranspiration data. Comparison of the criteria of performance of the various architectures of the neural network model showed that architecture 2-3-1 gives best results. This architecture provides Nash coefficients of 75.79% and correlation linear coefficient of 95.64% for the calibration and Nash coefficients of 73.32% and correlation linear coefficient of 98.33% for the validation. The correlations between simulated flows and observed flows are strong. The correlation coefficients are 83.89% and 83.08% respectively for the calibration and validation.

Keywords

Rain-Flow Modeling, Artificial Neural Network, Cavally River, Côte d'Ivoire

1. Introduction

The management of water resources constitutes a major stake for most of the countries in the world. For instance, the prevision of future hydrologic conditions is of capital importance in the planning and the management of water resources [1]. To predict flows, knowledge of the data on flows and/or past and present rains is necessary. However, the absence or the poor quality (gaps, measuring mistakes…) of hydro climatic data makes these hydrological studies difficult. Therefore filling of gaps is necessary before any use. Correlation methods between stations of same areas for filling gaps are often limited by the weak density of stations on the watersheds. The rain-flow model could bring an adequate solution to fill the gaps in the series of flow and rain data [2]. Indeed, the simulation of flow is one solution in the filling of gaps in the series of data, the reconstitution of historical flows. Owing to the difficulties to state nonlinear models, recent attempts resorts to artificial neurons networks (ANN) for the hydrological modeling of complex watersheds. Since early 1990s, artificial neurons networks have been used successfully in domains linked to hydrology such as the modeling of rain-flow, quality of water, strategy of water management, prevision of precipitation, hydrological chronological series [3], the estimation of non-measured floods [4], the prevision of typhoon-rain [5], the estimation of the flow of a river [6], for ameliorating the modeling rain-flow based on rainy events [7], the predictions of the chronological series of the height of rain [8], the modeling of the relation rain-flow [2]. Plus the distribution of Markov range for the probable distribution of rain in the lower watershed of the Bia [9]. Artificial neurons networks (ANNs) use dependent data. They do not impose any functional relation between independent and dependent variables in so far as this relation is terminated by the data in the learning process (or calibration) [10]. Mathematically, an ANN can be considered as universal approximation. For its capacity to learn and to generalize "the knowledge" of pairs of sufficient data artificial neurons networks can solve complex problems on big scale such as the recognition of forms, classification, association, check, nonlinear modeling and other problems [11]. This article aims to establish a model of rain-flow of the Cavally watershed of the hydrometric station of Ity in order to determine the flow and to fill the detected gaps in the series of the recorded historical data.

2. Material and Methods

2.1. Presentation of the Study Area

The Cavally River is a lower cross border watershed between Guinea, Ivory Coast and Liberia. Located in the west of Ivory Coast, the Cavally River begins in Guinea, in the North of Mount Nimba with more than 1000 meters as approximate altitude (**Figure 1**). 700 km long, its riverbed constitutes the border between Liberia and Ivory Coast from its middle way (at the South of Toulépleu) on about 330 km. The lower watershed covers a complete area of 28,800 Sq Km at Tate hydrometric station located at 60 km from the mouth. Côte d'Ivoire doesn't possess but about 15,000 Sq km of watershed [12]. In the framework of this study, the chosen outlet is the hydrometric station of Floleu located at

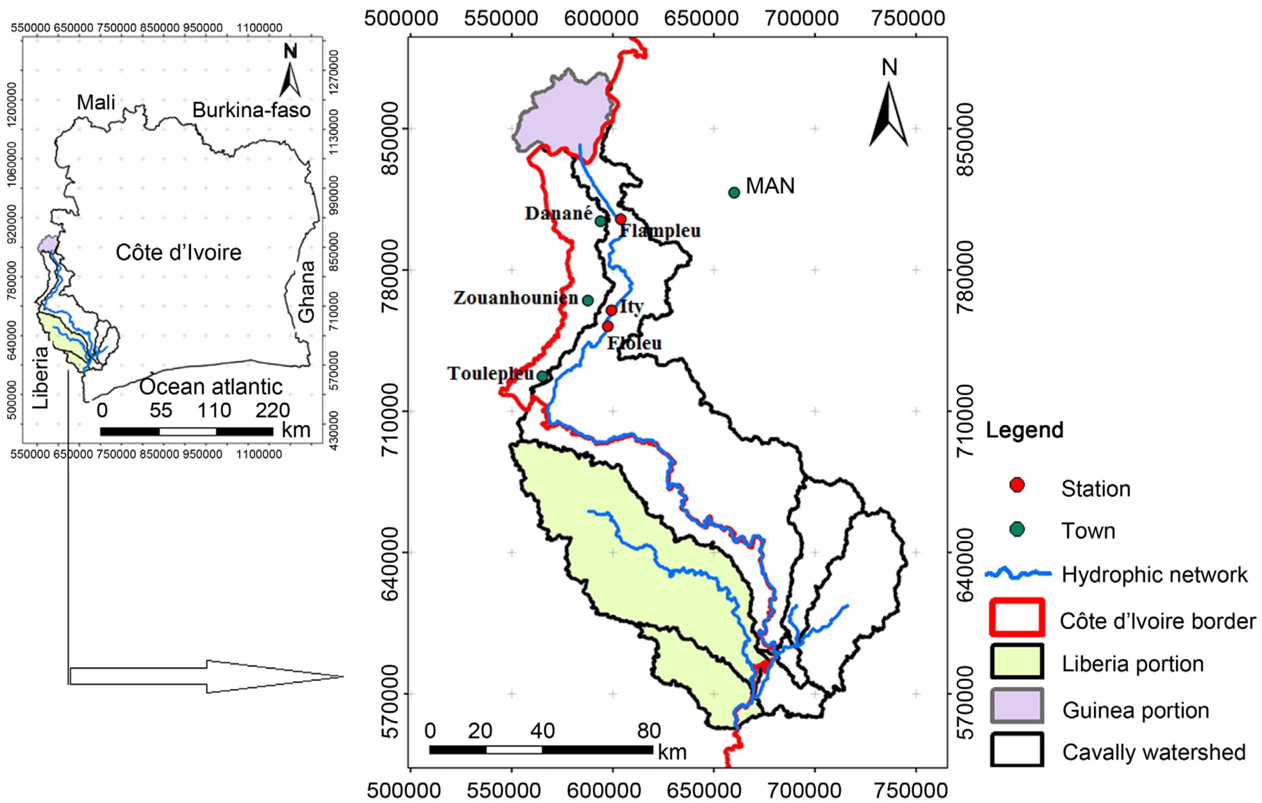


Figure 1. Study area of sub-watershed of Cavally River.

downstream of the Ity station in the Zouan-Hounien region. The low watershed has got an area of 3647.53 Sq km (**Figure 1**). The region of Zouan-Hounien is located in the mountain region of Côte d'Ivoire; its relief is hilly. Zouan-Hounien is located in the forest area and its climate is the mountain climate with two seasons: one rainy season from May to October and one dry season from November to March. The annual average temperature is 25.6˚C. The annual average precipitation is 186 mm. The driest month is January with a precipitation of 15 mm. The most important precipitations are recorded in September and they are 357 mm in average.

2.2. Data Acquisition and Analysis

The data used in the framework of this study are issued by three (3) hydrometric stations (Flampleu, Ity and Toulépleu) providing data about rain and temperature on the exploitation site of the Mining company of Ity (SM1). The daily data about flows are provided by the general office of infrastructures and human hydraulic (DGIHH) under the authority of the Ministry of Economic Infrastructures of the Republic of Côte d'Ivoire, whereas the data about monthly rains were acquired via the Company of development and Airport and Maritime exploitation (SODEXAM). To obtain the same pace of time like monthly rains, daily flows were transformed in monthly flows. These data cover the period from 1980 to 2001 for flows and from 1990 to 2007 for hydro-climate data. In order to permit the model to correctly simulate the provided data, a period of common basis was chosen by taking into account the quality of data that is to say with less gaps over a continuous period from August 1990 to December 2001. The potential monthly evapotranspiration was calculated by the formula of THORNTHWAITE (1994). The characteristic values are recorded in Table 1.

2.3. Rain-Flow Modeling Method by Neural Network

The setting of an artificial neural network constitutes four (4) steps: data search, pre-treatment of these data, learning and evaluation of the model. In this study, a perception of feed forwards retro propagation model with two layers, one hidden layer and one layer of exit was constituted (Figure 2).

To set neural network model, the data about average rain, ETP and flows on monthly pace on a continuous period from August 1990 to December 2001 were used. These data are firstly normed between the interval [0; 1] in order to permit an efficient treatment accepted by the in and out functions of the network [13]. The functions used for the normalization of the entry vector are given by the following relation [14].

$$X_N = \left(X - X_{\min}\right)\frac{X_{N\max} - X_{N\min}}{X_{\max} - X_{\min}} + X_{N\min} \tag{1}$$

X_N = normalized value corresponding to the elements of the entries vector (Rain, ETP), X = Real value of an element of the entries vector, $X_{\min}$ = minimum

Table 1. Hydro-climatic and flow data characteristics of Ity region.

	Flow (m^3/s)	Rain (mm)	Temperature (˚C)	ETP (mm)
Maximum	327.27	531.70	28	141.42
Average	143.69	151.37	25.76	85.9
Minimum	76.52	0.0	24	62.90
STDEVA	59.28	109.51	1.03	14.10

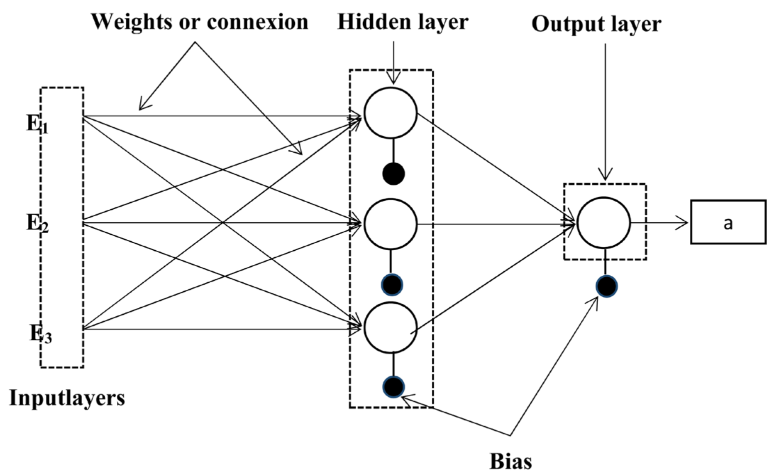


Figure 2. Multi-layers neuron network model.

value of an element of the entries vector, $X_{\max}$ = maximum value of an element of the entries vector, $X_{N\min}$ = minimum value of the normalization vector [0; 1] equal 0, $X_{N\max}$ = maximum value of the normalization vector [0; 1] equal 1.

These data are then subdivided in three (3) sub-sets: calibration, test and validation done respectively according to proportions of 50%, 30% and 20% equivalent respectively to 5; 3 and 2 years (**Figure 3**). A multi-layer perception of feed forwards model two (2) entries (average rain and ETP) and one exit (flows) with an architecture varying from one neuron to five hidden neurons. The network so constituted is trained in supervised way by an algorithm of second order (Levenberg Marquardt) according to retro propagation. In addition, to make converge rapidly the model, the weights and initial bias were fixed to 0, 1.

The programming was done under Matlab software R 2014 version. The artificial neural network developed in this study has the following characteristic:

- Mistake criterium: quadratic mistake.
- Activation function: Sigmoid function bounded from 0 to 1;
- Initial weights: 0, 1.
- Initial bias: 0.1;
- Number of iterations: 500.

The model is assessed with two (2) digital criteria (Nash coefficient and correlation coefficient) and graphic criteria (hydrograph of the observed and simulated of flows).

2.3.1. Nash Coefficient

In order to quantify the precision of the simulation and reliability of the model, Nash coefficient is applied on the obtained results [15]. Nash coefficient is then expressed by the following relation:

$$\text{Nash} = 1 - \frac{\sum_{i=1}^{n} \left(q_{oi} - q_{ci}\right)^2}{\sum_{i=1}^{n} \left(q_{oi} - \bar{q}_o\right)^2} \times 100 \tag{2}$$

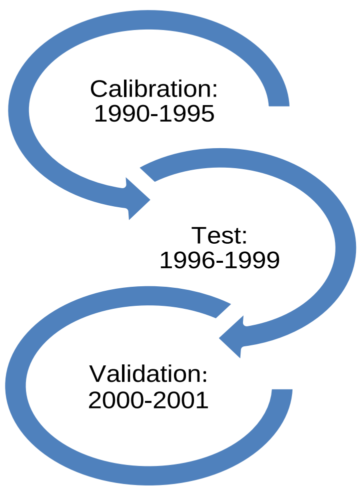


Figure 3. Process of data distribution into artificial neuron network model.

2.3.2. Correlation Coefficient

Noted R, the correlation coefficient on Pearson coefficient is the square root of the determination coefficient given by the relation:

$$R = \frac{\sum_i (q_{oi} - \overline{q}_o)(q_{ci} - \overline{q}_c)}{\sqrt{\sum_i (q_{oi} - \overline{q}_o)^2 \times \sum_i (q_{ci} - \overline{q}_c)^2}} \tag{3}$$

In these two expressions, n represents the height of the sequence, q_{oi} represents the observed flow for calculated flow for the pace time i in m^3/s; q_{ci}, is the calculated flow for the pace time i in m^3/s; $\overline{q}_o$ is the observed average flow in m^3/s.

3. Results and Discussion

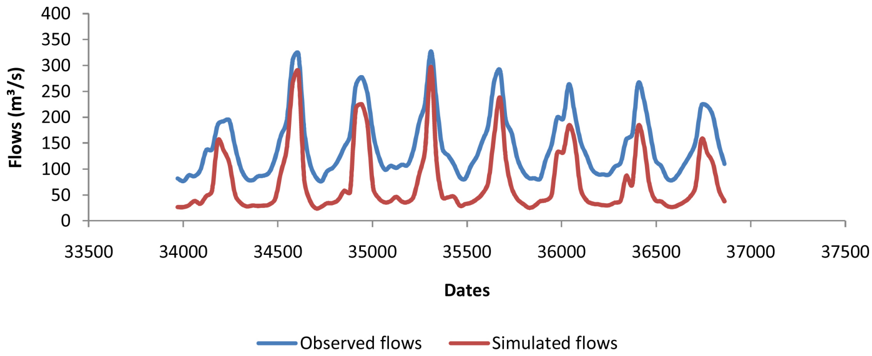
In modeling by neural network, to avoid an over learning (modeling of the raw), the obtained results are starting from the reserved data for learning must be validated on a new set of data. **Table 2** presents the criteria of estimation of the performance of the model in accordance with four [4] architectures (2-3-1; 2-4-1; 2-5-1 and 2-6-1) at the calibration and validation levels.

Observing this table, all the architectures given better performance criteria in accordance with the criteria of evaluation of the performance of a model, which must be higher than 60% for the Nash criteria and 80% for the correlation coefficient. However in the modeling of artificial neural network more the quantity of hidden layer is higher more the model becomes complex and unstable. To reduce this complexity of the model, it is necessary to choose the models which have fewer layers. There by the most appropriate model in the framework of this study is architecture model 2-3-1. So, the results of calibration and validation will be presented this way. **Figure 4** presents respectively the hydrographs and the correlation between the observed and the simulated flows by model 2-3-1 at the calibration level.

Although there are some gaps, model simulates better the flows. Indeed, gaps are noticed at the level of hydrographs of the observed and the simulated flows at the level of the calibration step of the model (**Figure 4**) but, Nash coefficient (75.79%) is for superior to 60% value from which a model can be considered efficient and stable. The linear correlation between the observed and the simulated flow sis strong with a correlation coefficient of 95.64% at the calibration level as

Table 2. Criteria of evaluation of artificial neural network the model performance for different structures.

			Structures of model			
			2-3-1	**2-4-1**	**2-5-1**	**2-6-1**
Criteria of valuation	NASH	Calibration	**75.79**	74.18	73.68	74.21
		Validation	**73.33**	74.64	74.02	73.75
	Correlation coefficient	Calibration	**95.64**	95.81	97.43	95.96
		Validation	**98.33**	98.4	96.93	98.86



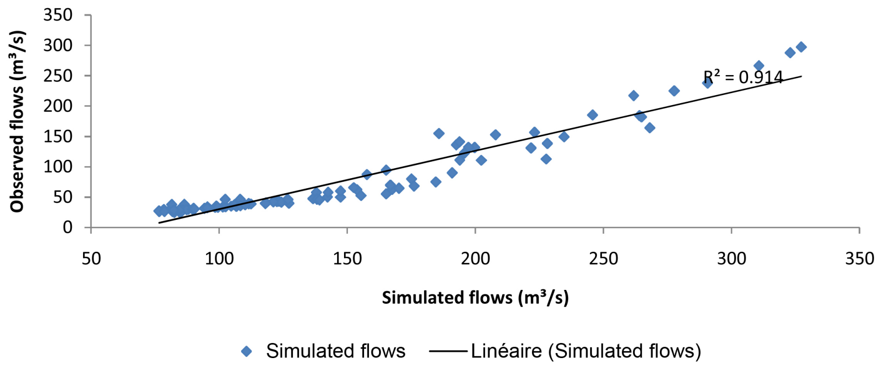


Figure 4. Hydrographs and graphical representation of the correlation between observed and simulated flow rates for the 2-3-1 structure of ANN model at the calibration level.

presented in **Figure 4**. **Figure 5** presents respectively flow hydrographs and the correlation between the observed and simulated flows by model 2-3-1 at the level of the validation model.

This step of validation model 2-3-1 presents Nash coefficients and respective linear correlation of 73.32% and 98.33%. These two criteria (Criterion of Nash and coefficient of correlation) allow appreciating the reliability and the stability of the artificial neurons network model. In effect, when the criterion of Nash is superior to 60% and the coefficient of linear correlation is superior to 80%, the model can be considered efficient. So, the analysis of the results shows that for three (3) hidden neurons, the model presents good performance criteria.

The **Table 3** summarizes performance criteria for the Artificial Neural Network model 2-3-1.

However, the tasks done [2] at the station of Bianouan on the river Bia revealed that the model with hidden neurons also gives interesting results with some criteria of Nash of 60.37% and the coefficient of correlation of 83.08% for validation. This difference in results could be explained by the density of the series of data for modeling which used a 26 year series of data whereas in this study the series of data is 10 years old. The model of neural network developed with the data of average rain, ETP calculated by the THORNTHWAITE method and the method of flow over the period from 1990 to 2001 gave good results with the architecture. Therefore, three (3) hidden neurons are necessary to well simulate flows at hydrometric station of Ity starting from two (2) entries (average

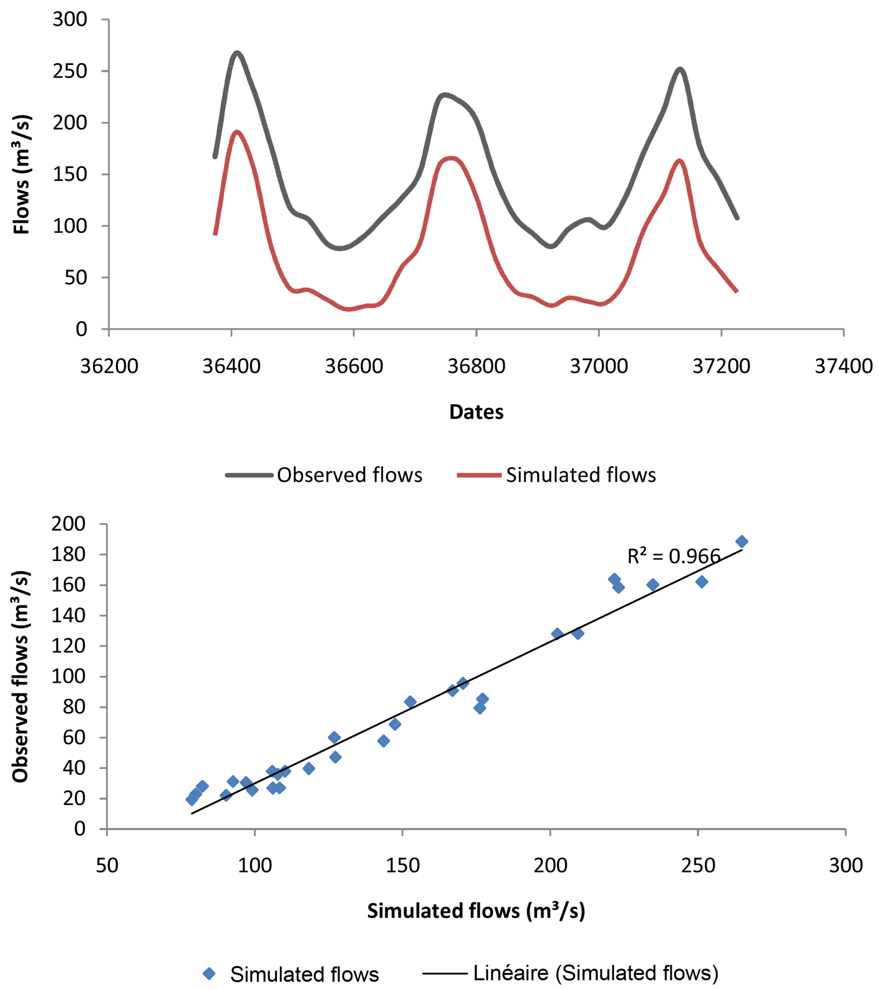


Figure 5. Hydrographs and graphical representation of the correlation between Observed (Qobs) and simulated (Qcal) flow rates for the 2-3-1 structure of ANN model at the validation level.

Table 3. Performance criteria for the artificial neural network model 2-3-1.

Criteria of evaluation	Calibration	validation
Criterion of Nash	75.79%	73.32%
Coefficient of correlation	95.64%	98.33%

rain and ETP calculated by the THORNTHWAITE). The tasks of [16] cited by [2] sunstroke and temperature and used with the average rain could simulate better the flows [17].

However, some gaps are noticed between the observed flows and the simulated flows by architecture 2-3-1 of the artificial neurons networks at the artificial neurons networks at the validation level. These differences can be explained by the fact that the artificial neurons networks are models which are influenced by the number of variables of entries model, the length of the series of data for the tuning and the quality of data. In fact, although the two variables of entries (average rain and ETP) well-simulate the flows at the station of Ity, the flows at this station are not only influence drain and ETP. According to [18]; [19] and [2], vegetation, the level of the stream, the capacity of retention of water of the soil, relief and the others losses are factors which influence the transformation of rain in flow. Consequently, [20] it is proven that by increasing the number of variables of entries of a model of artificial neurons network by one (1) to three (3) entries, the performance of the model improves considerably. The results obtained in this study (model 2-3-1) compared with those obtained (model 2-4-1) by [2] give approximately similar results. Since then, we could say that the number of neurons does not influence a lot the performance of the model to transform the rain in flow when comparatively with the quantity of data, the number entries data in the network.

4. Conclusion

This study allowed establishing a model of rain-flow thank to the artificial neuron network (multi-layer perception a feed forwards model) which is used to feel the gaps in the series of flows of the hydrometric station of Ity on the Cavally River. The results obtained through this model of artificial neuron network show that architecture 2-5-1 gives satisfactory results with 73.68% as Nash criterion at the tuning level and simulated flows of 97.43%, at test phase level a Nash criterion of 77.95%, and a very strong correlation of 98.42%, and the validation level a Nash criterion of 66.41% for a correlation between observed flows and simulated flows of 96.93%. This model will help in addition to the filling of gaps at the level rain data and flows, the evaluation of the impacts of anthropic activities on the down watershed of the Cavally River.

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