Larhyss Journal, ISSN 1112-3680, n°40, Dec 2019, pp. 27-43

DAILY AND INSTANTANEOUS FLOOD FORECASTING USING ARTIFICIAL NEURAL NETWORKS IN A NORTH-WEST ALGERIAN WATERSHED

PREVISION DES CRUES JOURNALIERES ET INSTANTANEES PAR LES RESEAUX DE NEURONES ARTIFICIELS D'UN BASSIN VERSANT DU NORD-OUEST D'ALGERIE

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ABSTRACT

In this paper, the use of Artificial Neural Networks (ANN) has been the subject of flood forecasting in the Oued Isser watershed located in North Western Algeria. The latter covers the largest Tafna's basin area with the most important wadi in the region.

Two models have been developed; the first one with data at a daily frequency and the second one with instantaneous data, the aim is to see which model represents the most the studied watershed in flood forecasting. Four criteria were used to judge the models performance, the NASH criterion, the coefficient of determination (R^2), the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE).

The results obtained show that the two models perform well with the specific features of each and can in this case be used together, improving the effectiveness of flood forecasting.

Keywords: Flood forecasting, Artificial Neural Networks, Oued Isser Basin, daily data, instantaneous data.

RESUME

Dans cet article, l'utilisation des Réseaux de Neurones Artificiels (RNA), connus pour leur capacité à modéliser les systèmes non linéaires, a fait l'objet de la prévision des crues dans le bassin versant de l'Oued Isser. Ce dernier est situé dans le Nord-Ouest d'Algérie et couvre la plus grande superficie du bassin de la Tafna avec l'Oued le plus important de la région.

Deux modèles ont été développés, le premier avec des données à pas de temps journalier et le second avec des données instantanées, l'objectif est de voir lequel des deux modèles représente le plus le bassin versant étudié en prévision des crues.

Quatre critères ont été utilisés pour juger la performance des modèles, le critère de NASH, le coefficient de détermination (R^2), l'erreur quadratique moyenne (RMSE) et l'erreur absolue moyenne (MAE).

Les résultats obtenus montrent que les deux modèles fonctionnent bien avec les spécificités de chacun, et peuvent dans ce cas être utilisés ensemble, améliorant ainsi l'efficacité de la prévision des crues.

Mots clés : Prévision des crues, Réseaux de Neurones Artificiels, bassin de l'Oued Isser, données journalières, données instantanées.

INTRODUCTION

Flooding in Algeria are often the result of torrential rains that manifest in a brutal way, causing a lot of damage which costing the country very dearly. It is still fresh in the Algerian's minds the floods of 2018 in Constantine and Tebessa, two cities situated in the East of Algeria, where three people died, many wounded and large-scale material damage, in addition to the post-disaster trauma of the population.

In general, this type of floods happens in autumn and spring as is the case of the studied watershed, called Oued Isser basin. According to Ketrouci et al. (2012), seventy-six percent of the floods observed in this basin occur during these inter-season periods.

Oued Isser, like all other temporary streams, turns into torrents in case of sudden rain showers that can cause important and devastating floods. Referring to the world repertoire of observed maximum floods (Rodier and Roche, 1984), Oued Isser used to overflow following heavy rainfall; the most significant floods were on April, 16, 1954 with a flow of 1140 $m^3 s^{-1}$ and on March, 29, 1973 with a flow of 1110 $m^3 s^{-1}$.

The construction of the dam 'El Izdihar' at the outlet of the basin commissioned in 1988 for agricultural purposes has not secured the region. In 2009, heavy rains which fallen in the region for several days have caused the overflow of Oued Tarenne (a tributary of Oued Isser) and caused significant material damage.

In the face of these natural disasters, it is commonly agreed that flood forecasting remains the most favorable way. This forecast includes everything from floods risk mapping, announcement service of floods, and also hydrological modeling. Numerous streamflow forecasting techniques have been suggested and used in the past. They generally fall under statistical/stochastically based and conceptual/physically based techniques (Salas et al. 2000).

From the 1990s onwards, many researchers in hydrology have been interested in floods prediction by Artificial Neural Networks (ANN). This method takes its origin in an inspiration from the biological neural network, one of the features of ANN cited by Deo and Thirumalaiah (2000) is that neural networks are useful when the underlying problem is either poorly defined or not clearly understood.

Several studies have been done in the field of hydrological forecasting using ANN, for example French et al. (1992), Luk Kin et al. (2001) worked on rainfall forecasting; Karunanithi et al. (1994), Dawson and Wilby (1998), Rajurkar et al. (2002), Santos and Silva (2013), Alexis et al. (2017) used the neural-network approach in the flow forecasting.

It should be noted that, Piotrowski et al. (2012) used the Product-Units Neural Networks (PUNNs) a subclass of higher order neural networks in hydrology for the first time in 2012.

In this paper, it is planned to create two Multi Layer Perceptrons (MLP) with backpropagation algorithms of the gradient, with as inputs precipitations, evapotranspirations and observed streamflows for the first one, water heights and instantaneous discharges for the second one. The main objective is therefore to identify which model represents the most the Oued Isser watershed in flood forecasting.

MATERIEL AND METHODS

Study watershed presentation

The Oued Isser catchment area is 1140 km^2; it is the largest sub-basin of the Tafna watershed located in the North-West of Algeria. The region's climate is Mediterranean, semi arid with temperate winter. The Oued Isser, which is the most important tributary, both by its length and its high flow, originates in the secondary massif of Tlemcen, in the territory of Beni Smiel (Gentil, 1901) at an altitude of 1625 m. The flow is regulated by El Izdihar dam located in the basin's outlet at an altitude of 275 m.

The studied basin has a dense hydrographical network where the wadi receives the two main affluents: Oued Chouly on the left bank and Oued Bouhadi on the right bank. Other large wadis flow into the Oued Isser as Oued Cedra on the right and Oued Sikkak which comes from the wadi Meffrouch on the left (figure.1).

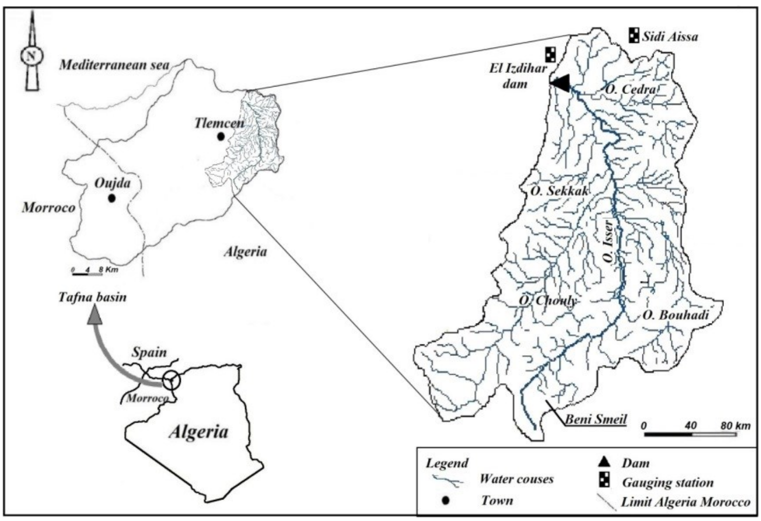

Figure 1. Location of the Oued Isser basin

The slope of the ground exceeds 30 percent over nearly 32 percent of the catchment area (Mazour, 1992). The vegetation cover is sometimes in the form of extensive crops and arboriculture and sometimes degraded to bare ground. The average of annual precipitations is in the order of 380 mm for the period from 1983 to 2013, rainfall is erratic with a coefficient of variation of 0.23. The average annual temperature is 18 °C recorded at the El Izdihar dam station; the lowest temperatures are felt in the months January and December, while the maximum is in July with an average of 28.6 °C.

Artificial Neural networks (ANN)

Towards the end of the 19th century, ANNs first appeared in the form of general theories based on research in physics, neurophysiology and psychology. During the 1940s, Warren Mc Culloch and Walter Pitts revealed that the resolution of any arithmetic and logical function can be done easily with neural networks. Their comments were supported by Donald Hebb's proposition of the basic principle of learning in the late 1940s.

Rosenblatt (1958) proposed a model of a simple neuron network composed by a layer of inputs and a layer of outputs that he called a Single Layer Perceptron (SLP) whose goal was to recognize the forms and which was later proved to be very limited. At the same time, Bernard Widrow and Ted Hoff proposed a new learning algorithm similar to perceptron, which was widely criticized and led to the abandonment of research on neural networks.

It was only in the early 1980s, with the development of the computer tool that researches resumed, Rumelhart et al. (1986) developed a multi-layered neuron network that they have named MLP (Multi-Layered Perceptron) with a feed forward backpropagation algorithm.

It is from this moment that the neural networks have taken their place as a means of solving all kinds of problems by their flexibility to solve nonlinear problems. Other than the SLP and the MLP, there are several types of neural networks such as Recurrent Neural Network (RNN), Self Organizing Map (SOM), Time Delay Neural Network (TDNN).), Radial Basis Function (RBF), etc.).

The most popular and most used is the MLP which is part of the family of feedforward artificial neural network, it is usually formed by a layer of inputs, one or more hidden layers and a layer of outputs, it utilizes a supervised learning technique called backpropagation for training. In recent years, there is a trend towards deep learning which is a particular way used when there are several hidden layers.

Neural networks with at least one hidden layer are necessary and sufficient for arbitrary nonlinear function approximation (Zhang and Gupta, 2000) and hence, for forecasting of floods. The neuron that will be developed in this case consists of three layers: an input one, a hidden one whose number of neurons will be determined by the trial error process and an output one (Figure 2).

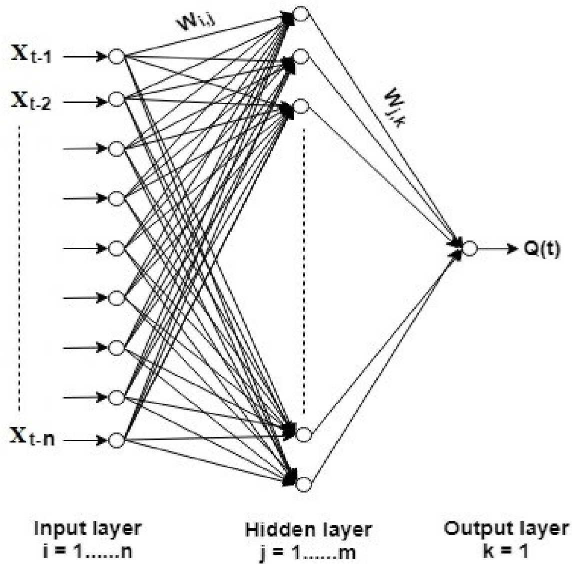

Figure 2. Architecture of the developed neurons with three layers

1. Each node of the input layer is connected with all the neurons of the hidden layer by a link with a weight Wij. Each neuron in the hidden layer makes a summation of the product of the inputs and the corresponding weights:

$$a_j = \left(\sum_{i=1}^{n} w_{i,j} . x_i \right) \tag{1}$$

Where $w_{i,j}$ are the connection weights between i input and j neuron and x_i are the input signals.

2. The weighted sum of each neuron is activated by an activation function A(α):

$$f(a_j) = A(\alpha) \times \left[\left(\sum_{i=1}^{n} w_{i,j} . x_i \right) \right] \tag{2}$$

The chosen function for the hidden layer is the logistic sigmoid that performed the best, the range of output values of this function is [0, 1] and is given by:

$$A(\alpha) = \frac{1}{1 + \exp^{-\alpha}} \quad (3)$$

3. The activated sum is then connected to the neuron of the output layer by a link with a weight $W_{j,k}$ activated by a simple linear function that compute the weighted sum.

The network will be trained with Levenberg-Marquardt backpropagation algorithm where the training stopped until some stopping criterion is satisfied. The codes are generated using MATLAB version R2015a.

The performance of the developed models is measured by numerical criteria, Chai and Draxler (2014) cited that a combination of metrics, including but certainly not limited to RMSEs and MAEs, are often required to assess model performance. In addition to these two criteria, the numerical evaluation of the developed models quality is based on two other criteria equally important, the Nash and Sutcliffe (1970) criterion and the coefficient of determination R^2. The formula for each criterion is given below:

1 - The Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{n}\left(Q_{obs}(t) - Q_{sim}(t)\right)^2} \quad (9)$$

2 – The Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum |Q_{obs}(t) - Q_{sim}(t)| \quad (10)$$

3 – The Nash and Sutcliffe (1970) criterion

$$NASH = 1 - \frac{\sum_{t=1}^{n}\left(Q_{obs}(t) - Q_{sim}(t)\right)^2}{\sum_{t=1}^{n}\left(Q_{obs}(t) - \overline{Q}_{obs}\right)^2} \quad (11)$$

4 - The coefficient of determination (R-squared, R^2)

$$R^2 = \left[\frac{N\sum Q_{obs}(t) \times Q_{sim}(t) - \sum Q_{obs} \times \sum Q_{sim}}{\left[\left(N\sum Q_{obs}{}^2 - \left(\sum Q_{obs}\right)^2\right)\right] \times \left[\left(N\sum Q_{sim}{}^2 - \left(\sum Q_{sim}\right)^2\right)\right]}\right]^2 \quad (12)$$

Where $Q_{obs}(t)$ is the observed streamflow in time t; $Q_{sim}(t)$ is the simulated streamflow in time t and $\bar{Q}_{obs}$ is the average observed streamflow over the evaluation period N.

Input data

The data used in this study come from two stations, the first one is the El Izdihar dam station (X: 152,5 Km and Y: 199,8Km) (station A) located at the basin outlet where registrations are done daily and the second one is the Sidi Aissa station (X: 157.3 Km and Y: 199.5 Km) (station B) very close to the dam, the measurements are done in a continuous way.

The station (A) data are in the form of observed precipitations, streamflows and temperatures spread over a period from 1983 to 1993.

The rainfall data constitute a sample of maximum daily rainfall for each year with a coefficient of variation of 5.71 reflecting a great irregularity of the daily rainfall regime. Flow rates are directly related to rainfall, there are a low water period during the summer and a period of high water mostly in spring and autumn.

Temperatures are too high in the summer and reach the maximum in July with a value of 28.6°C, the average annual temperature is 18°C and the minimum is generally in January which can be less than zero.

The evapotranspiration (PE) which is a function of temperature is computed based on the Oudin et al. (2005) formula. The latter gives, according to the authors, results as efficient as formulas more complex and more demanding in data such as Penman (1948) formula, it is written as follows:

$$PE = \frac{R_e}{\lambda\,\rho}\frac{T_a}{100} \qquad if \qquad T_a + 5 > 0$$

$$PE = 0 \qquad\qquad \text{Otherwise} \qquad (4)$$

Where PE is the rate of potential evapotranspiration (mm day^{-1}), Re is extraterrestrial radiation (MJ m^{-2} day^{-1}), λ is the latent heat flux in (MJ kg^{-1}), ρ is the density of water (kg m^{-3}) and Ta is mean daily air temperature (°C), derived from long-term average.

The extraterrestrial radiation (Re) as defined by Allen et al. (1998) is the solar radiation received at the top of the earth's atmosphere on a horizontal surface. The formula (5) estimates the extraterrestrial radiation for each day of the year for different latitudes.

$$Re = \frac{24(60)}{\pi} G_{sc} d_r [\omega_s \sin\varphi \sin\delta + \cos\varphi \cos\delta \sin\omega_s] \quad (5)$$

Where Re is the extraterrestrial radiation [MJ m^{-2} day^{-1}], G_{sc} is the solar constant (G_{sc} = 0.0820MJ m^{-2} min^{-1}), d_r is the inverse relative distance Earth-Sun calculated by:

$$d_r = 1 + 0.033 \cos\left(\frac{2\pi}{365} J\right) \quad (6)$$

Where J represents the number of the day in the year between 1 (1 January) and 365 or 366 (31 December), ω_s is the sunset hour angle [rad] calculated by:

$$\omega_s = arc\cos(-\tan\varphi \tan\delta) \quad (7)$$

Where φ is the latitude [rad], and δ is the solar decimation [rad] calculated by:

$$\delta = 0.409 \sin\left(\frac{2\pi}{365} J \times 1.39\right) 1 + 0{,}033 \cos\left(\frac{2\pi}{365} J\right) \quad (8)$$

The simulation period for the daily time step extends from 01/01/1983 to 31/12/1993, the part stretching from 01/01/1983 to 31/12/1991 is used to learn the developed neuron where 70 percent is for the training and 30 percent is for the validation and the last two years are used for forecasting. The input vector is represented by the previous three days (t - 1, t - 2, t - 3) for a total of nine (9) inputs (P_{t-1}, P_{t-2}, P_{t-3}, EP_{t-1}, EP_{t-2}, EP_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3}).

The station (B) data are in the form of water heights and instantaneous discharges from 15/09/1988 to 29/06/2004. The dataset shows six (6) significant floods with flows greater than 100 m^3s^{-1}, the maximum is about 295.4 m^3s^{-1} which occurred mainly in spring and autumn. The other floods are mostly less than 50 m^3s^{-1}.

The simulation period for the instantaneous data starts from 15/09/1988 to 01/12/2000, from the begin to 01/12/2000 are for the learning phase where 70 percent is for the training and 30 percent is for the validation and the last part (03/12/2000 to 29/06/2004) is for the forecasting phase. The input vector is represented by the previous four days (t - 1, t - 2, t - 3, t - 4) for a total of eight inputs (H_{t-1}, H_{t-2}, H_{t-3}, H_{t-4}, Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}).

RESULTS AND DISCUSSION

The number of hidden neurons obtained by trial error process which gave the best simulation is nine (9) for the station A and eleven (11) for the station B. The results are shown in table 1, figures 3, 4, 5, 6, 7 and 8.

Table 1. Performance criteria for learning and forecasting phases of the two stations

	El Izdihar dam station (A)				*Sidi Aissa station (B)*			
	NASH	**R^2**	**RMSE**	**MAE**	**NASH**	**R^2**	**RMSE**	**MAE**
Learning	0.76	0.78	0.74	0.12	0.71	0.70	10.63	3.45
Forcasting	0.65	0.68	0.51	0.14	0.61	0.62	6.43	3.08

RMSE and MAE reveal a good forecast when they are low, so the forecast is perfect when the values of these criteria are zero. The Nash criterion and the coefficient of determination are good when they tend to 1.

For the learning phase, the results obtained for the station (A) show a good simulation with values of NASH and R2 criteria exceeding 70 percent and MAE does not exceed 20 percent while the RMSE is large enough.

The forcasting phase gives good results too, NASH and R^2 are almost similar as the learning phase and close to 70 percent and MAE is 14 percent. The RMSE in this phase is acceptable with a value of 51 percent which shows a suitable quality of prediction.

Graphically, the simulated and observed streamflows for the learning phase coincide well except for the first high streamflow (12/11/1984) where there is a significant gap and where the flow rate is underestimated (Figure 3). It may be due to the fact that it is the first high streamflow after an extended low flow period. It is this value that has distorted the most RMSE, bearing in mind that this criterion is relevant to high flow values as mentioned by Sundara Kumar et al. (2016). The forecasting phase is well represented over the entire simulation period, which is in line with the good results of the performance criteria (figure 4).

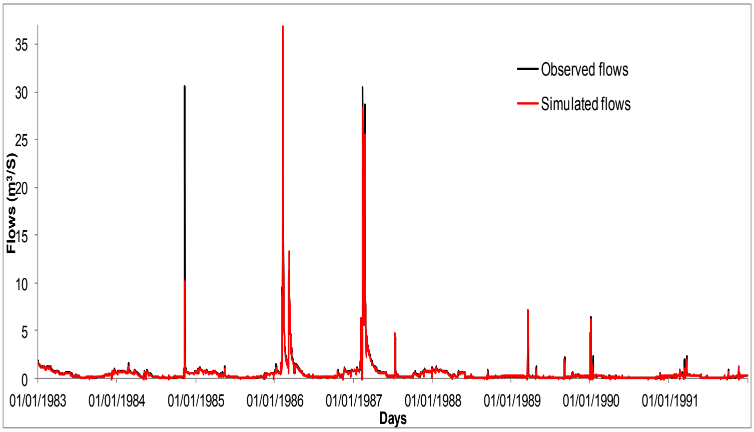

Figure 3. Simulated and observed flows of the Oued Isser basin during the learning phase (station A)

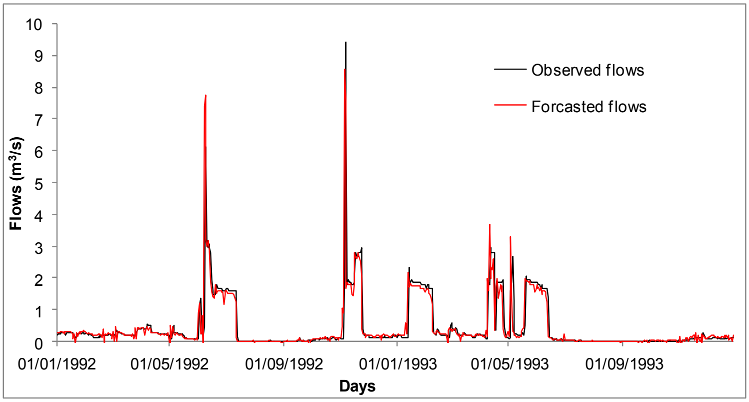

Figure 4. Simulated and observed flows of the Oued Isser basin during the forecasting phase (Station A)

For further clarity, the results are presented in the form of a scatterplot of the simulated flows vs. the observed flows (Figure 5), the correlation is satisfactory with a coefficient of correlation of 0.89 for the learning phase and 0.82 for the forcasting phase. There are some points that are far from the ideal line, the flows are sometimes overestimated and sometimes underestimated but roughly the scatterplot is well spread over the ideal line.

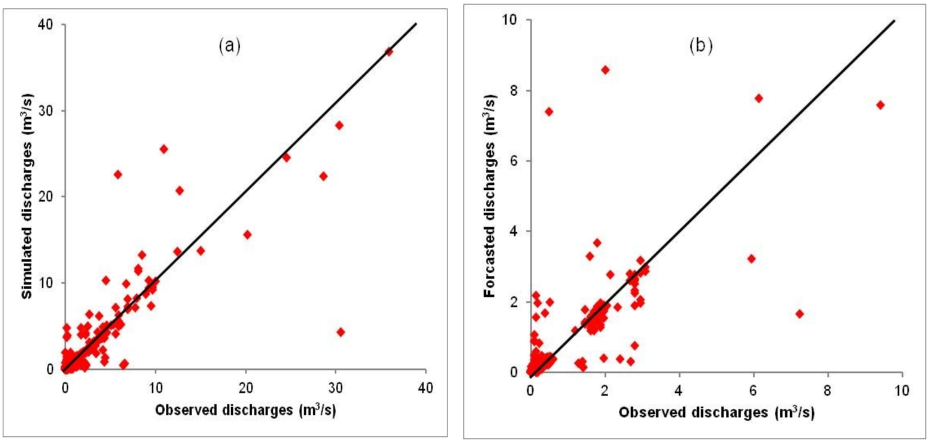

Figure 5. Simulated flows vs. observed flows for the learning (a) and forecasting (b) of the station A

For the station B, the learning phase gave NASH and R2 criteria almost similar that the station A with values of 0.71 and 0.70 respectively reflecting a good simulation while MAE and RMSE coefficients are very bad. Chai and Draxler (2004) cited that the underlying assumption when presenting the RMSE is that the errors are unbiased and follow a normal distribution, two conditions difficult to meet when it comes to floods where climatic conditions are very variable.

They also quoted that giving higher weighting to the unfavorable conditions, the RMSE usually is better at revealing model performance differences. Indeed, the excessive value of RMSE can reveal a great variability of the instantaneous data confronted with exceptional events thus giving more information compared to the results obtained with the daily data where the forecast is more precise but less informative.

Graphically, it is the contrary to the trends noted for the Station (A), the first high flow was simulated very well which supports the assumption that after a long period of low flows, the first high flow can be biased. The same explanation can be given to the underestimation of the flow of 06/10/1997 in the learning phase (Figure 6).

The figure 7 shows that the forecasting of large flows is better than that of small flows, which is incompatible with the value of the RMSE criterion which should have been good instead of bad, suggesting that RMSE criterion and probably the MAE criterion are not representative in the instantaneous time step.

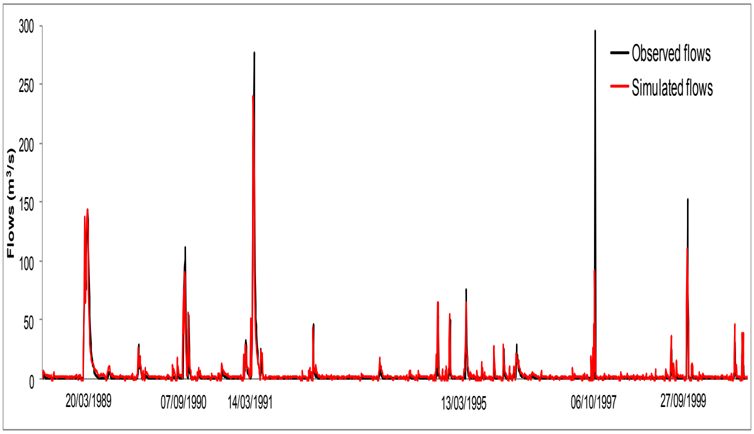

Figure 6. Simulated and observed flows of the Oued Isser basin during the learning phase (station B)

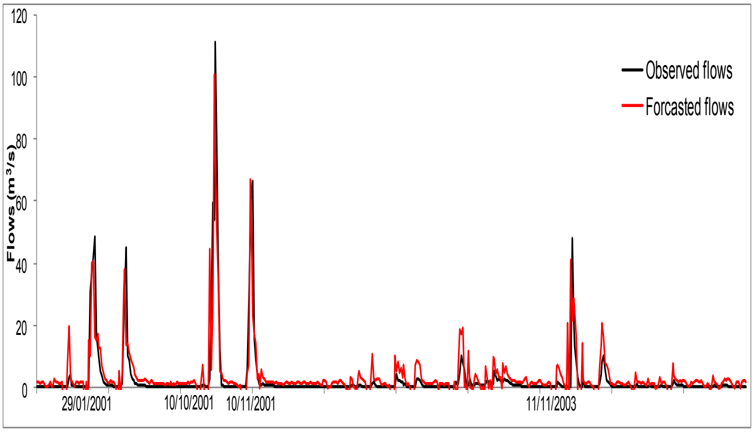

Figure 7. Simulated and observed flows of the Oued Isser basin during the forecasting phase (Station B)

The scatterplot of the simulated flows vs. the observed flows (Figure 8) shows a good correlation with a coefficient of correlation of 0.84 for the learning phase and 0.79 for the forcasting phase.

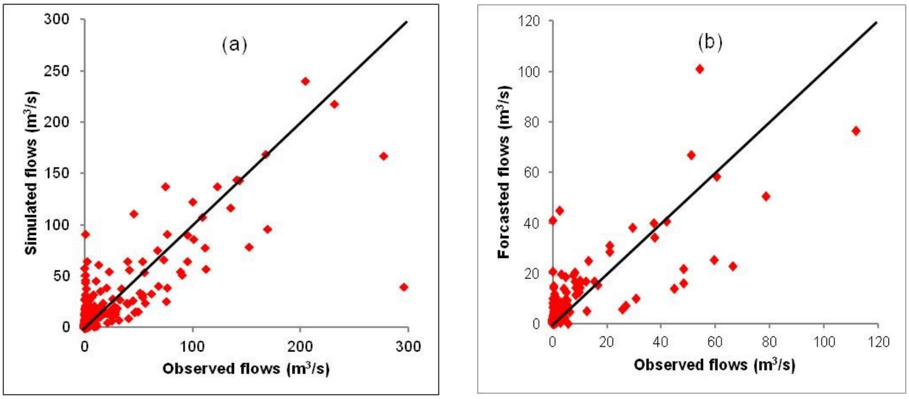

Figure 8. Simulated flows vs. observed flows for the learning (a) and forecasting (b) of the station B

From the foregoing it appears that the model with daily time step is more efficient than that with the instantaneous data by comparing numerical criteria. Graphically, one is as efficient as the other and each can provide details that can help improve flood forecasting.

CONCLUSION

The present paper was about the development of floods forecasting models using ANN applied to a watershed located in North West of Algeria with two gauging stations. A station with daily step data (station A) and the other one with instantaneous data (station B).

The chosen models were the Multi Layer Perceptron with three layers:

- A layer of nine (9) inputs for the station A and eight (8) inputs for the station B,
- A layer of nine (9) hidden neurons for the station A and eleven (11) for the station B determined by trial error process and activated by a logistic Sigmoid function,
- A layer of one output for the two stations activated by a simple linear function and gave the forecasting flows.

The performance was tested by four numerical criteria: NASH, R^2, MAE and RMSE in addition to the visual appearance and the correlation coefficients between observed and simulated flows.

For the station A, the four numerical criteria values were acceptable and revealed that the model was satisfactory in learning and more in forecasting since the RMSE was less good in learning. The graphical representation showed a good agreement between the simulated and observed flow rates with correlation coefficients greater than 80 percent.

For the station B model, the two criteria NASH and R^2 gave good results whereas the MAE and RMSE were too bad in learning and forecasting despite a graphical representation revealing a good simulation of flows where the correlation coefficients were 0.84 for the learning phase and 0.79 for the forecasting phase.

In sum, the developed models gave good results and could be used in floods forecasting taking into account the failure and the reliability of each, and hence both models can be used in complementarily.

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