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Adaptive neural fuzzy inference systems for the daily flow forecast in Algerian coastal basins

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ABSTRACT

Exceptional hydrological events represent one of the most important natural risks which are responsible for the loss of human lives and material goods. During recent decades, many automated or computerized approaches have been implemented to model this process. However, the complexity of hydrological regimes requires the use of specific tools for dynamical and non-linear systems. In order to model the rainfall–runoff transformation, we propose the employment of an adaptive neural network-based fuzzy inference system to predict the flow at the outlet of Algerian coastal basins. The neural network-based fuzzy inference system can be considered as an unlooped neural network for which each layer is a component of a neuro-fuzzy system. The obtained results show that the performances of neuro-fuzzy models exceed those of neural network models and classical multiple linear regression models.

Keywords: Prediction; Flow; ANFIS; Coastal Basins; Algeria

1. Introduction

Modeling the hydrological behavior of watersheds is essential when one is interested in issues related to flood disasters; these exceptional hydrological events are one of the most important natural hazards which are sometimes responsible for the loss of lives and material goods. The transformation of rainfall into runoff results from a number of complex mechanisms that occur simultaneously at different scales [1]. Thus the rainfall-runoff model is its necessity to the extent that the model developed from a series of observed rainfall can generate flow rates that are as close as possible to rates observed that is to say from observations of rainfall, may be able to predict the response of the basin flow. In recent decades, a large number of automated or computerized approaches have been implemented to model this process. However, the

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complexity of hydrological regimes requires to use specific tools of non-linear dynamical systems [2].

As such, our aim is to model the transformation of rainfall into runoff using an Adaptive Network-based Fuzzy Inference System for flow forecasting [3]. The value of building prediction systems integrating neural networks and fuzzy inference systems lies in their complementary characteristics. The fuzzy inference systems exploit linguistic rules reflecting knowledge about the system dynamics. The performance of these models in non-linear modeling has been proven in several areas of engineering and science. The most recent studies using neuro-fuzzy systems to model the rainfall–runoff relationship for example are those of the authors in references [4–7].

2. Adaptive neuro-fuzzy inference system

Adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference system implemented in the framework of adaptive networks; the first appearance of this system was by Jang [3,8]. It uses the hybrid learning procedure. This architecture refines the fuzzy rules obtained by human experts to describe the input–output behavior of a complex system.

ANFISs are hybrid systems using the Takagi–Sugeno–Kang fuzzy inference [9,10]. To simplify the model, we consider a system with two inputs x_1 and x_2, one output y, and a Sugeno type fuzzy model, composed of the following two rules:

$$\begin{aligned}&\text{Rule 1 : If } (x_1 \text{ is } A_1) \text{ and } (x_2 \text{ is } B_1)\\&\text{then } (F_1 = a_0^1 + a_1^1 x_1 + a_2^1 x_2)\end{aligned} \tag{1}$$

$$\begin{aligned}&\text{Rule2 : If } (x_1 \text{ is } A_2) \text{ and } (x_2 \text{ is } B_2)\\&\text{then } (F_2 = a_0^1 + a_1^1 x_1 + a_2^1 x_2)\end{aligned} \tag{2}$$

Jang [3] proposed to represent the rule-based adaptive network shown in Fig. 1.

The adaptive network ANFIS is a multilayer network whose connections are not weighted or they all have a weight equal to one [8]. Nodes are of two types according to their functionality: adaptive nodes (square) and fixed nodes (circular). Output O_i^k of node i of layer k (called node (i, k) depends on signals from the layer k-1 and the parameters of the node (i, k).

Layer 1: It allows the inclusion of data.

Layer 2: This layer allows the fuzzification of the variables x_1 and x_2. It characterizes the degree of membership O_i^k of x with respect to fuzzy sets.

Layer 3: Layer 3 generates the degree of activation of a rule.

Layer 4: The output of node i characterizes the normalized degree of activation of rule i.

Layer 5: The output of each node in Layer 4 is determined by the output of rule i.

Layer 6: This layer is represented by a single node level is what sums the signals from Layer 5.

The ANFIS network uses, on the one hand, a fuzzy algorithm coalescence of all the data to partition the input space. It uses, on the other hand, a learning algorithm by back propagation in order to simplify the finding and to eliminate the irrelevant input variables [11].

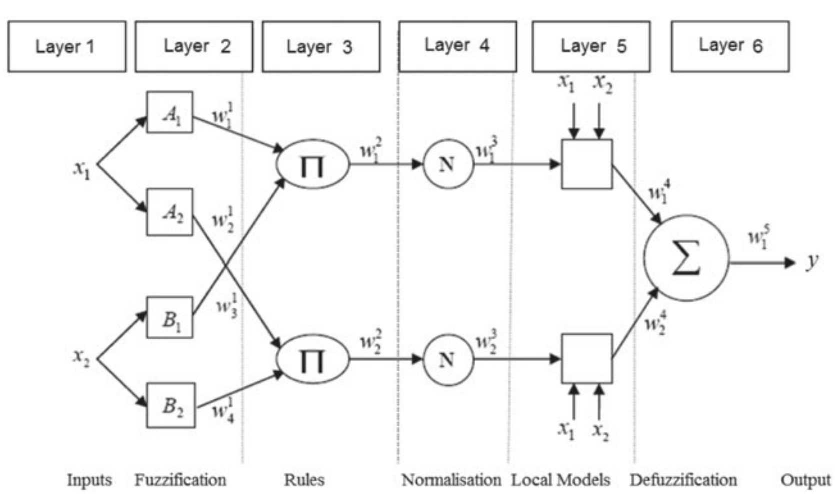

Fig. 1. General architecture of an ANFIS network.

3. Performance indicators

The performance of the ANFIS model is validated by statistical parameters of the phases of training, validation, and test. The statistical parameters used in this work are: the average squared error (ASE), the Nash–Sutcliffe coefficient of efficiency (CE) [12], and the correlation coefficient (r). These parameters are given by the following relations:

$$\mathrm{ASE} = \sum_{i=1}^{N} (Qt_i - \hat{Q}t_i)^2 / N \quad (3)$$

$$\mathrm{CE} = 1 - \frac{\sum_{i=1}^{N} (Qt_i - \hat{Q}t_i)^2}{\sum_{i=1}^{N} (Qt_i - \overline{Q}t)^2} \quad (4)$$

$$r = \frac{\sum_{i=1}^{N} (Qt_i - \bar{Q}t)(\hat{Q}t_i - \tilde{Q}t)}{\sqrt{\sum_{i=1}^{N} (Qt_i - \overline{Q}t)^2 \sum_{i=1}^{N} (\hat{Q}t_i - \tilde{Q}t)^2}} \quad (5)$$

where Qt_i is the measured flow rate value, $\hat{Q}t_i$ is the flow rate calculated by the model, $\bar{Q}t$ is the average flow measured, $\tilde{Q}t$ is the average flow simulated, and N is the number of data.

4. Hydrological forecasting

The database contains values of rainfall and runoff in two small Algerian coastal watersheds (Fig. 2). The first basin is the Bordj Ghobrini, located in the north-center of the country. It is coded 02-03 by the National Agency of Water Resources. The basin is drained by the Wadi Hachem. The data correspond to the period of seven years of daily observations of rainfall and runoff from 1 January 1983 to 31 December 1989.

The second basin considered in this study is that of Turgot, there is also an exoreic basin located in the northwestern Algeria in the region of Ain Temouchent coded 04-02 (Fig. 2), it is drained by the Wadi El Mellah. In this basin, we have the hydrometric station Turgot North located downstream and coded 04-02–20 by the National Agency of Water Resources, and rainfall station of Wadi Berkech coded 04-02–03. For both stations, we have two sets of data obtained from seven years of daily observations sampled without any gaps, spanning from 1 January 1990 to 31 December 1996.

The input parameters of ANFIS model are the values of flow and rainfall observed at previous times, only P_{t+1} corresponds to the rain predicted. Consequently, the output of the network represents the expected value of flow for the day $t+1$.

The database was divided into three sets: training, verification, and testing.

The three data-sets were subdivided as follows:

- a set for the training phase of the model corresponding to 70% of the data;
- the other set for the verification phase of the model corresponding to the remaining 30%; and
- all of the data (100%) were used for the test phase of the model.

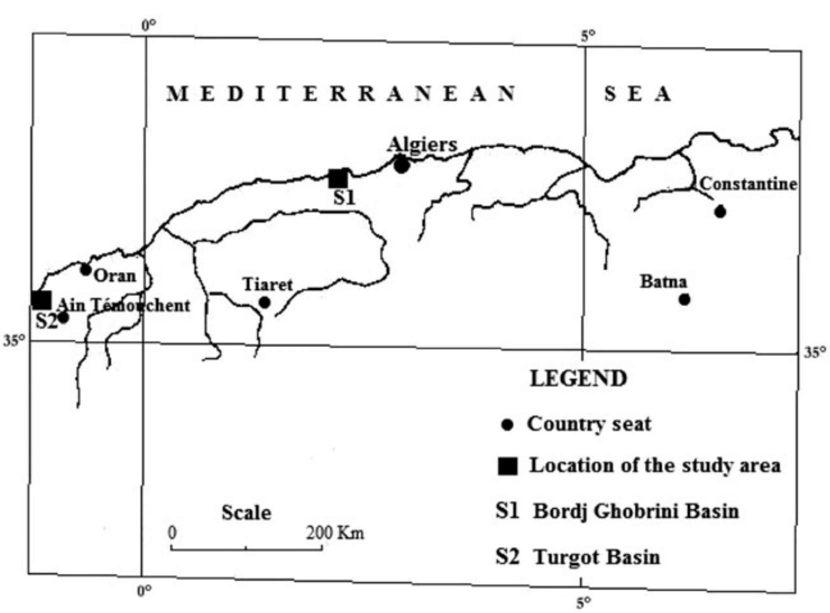

Fig. 2. Geographical location of study seats.

Table 1
ANFIS model structure with input vectors

Models	ANFIS model inputs
I	$Q_{t+1} = \text{ANFIS}(P_t, P_{t+1}, Q_t)$
II	$Q_{t+1} = \text{ANFIS}(P_t, P_{t+1}, Q_{t-1}, Q_t)$
III	$Q_{t+1} = \text{ANFIS}(P_t, P_{t+1}, Q_{t-2}, Q_{t-1}, Q_t)$
IV	$Q_{t+1} = \text{ANFIS}(P_t, P_{t+1}, Q_{t-3}, Q_{t-2}, Q_{t-1}, Q_t)$
V	$Q_{t+1} = \text{ANFIS}(P_t, P_{t+1}, Q_{t-4}, Q_{t-3}, Q_{t-2}, Q_{t-1}, Q_t)$
VI	$Q_{t+1} = \text{ANFIS}(P_t, P_{t+1}, Q_{t-5}, Q_{t-4}, Q_{t-3}, Q_{t-2}, Q_{t-1}, Q_t)$
VII	$Q_{t+1} = \text{ANFIS}(P_t, P_{t+1}, Q_{t-6}, Q_{t-5}, Q_{t-4}, Q_{t-3}, Q_{t-2}, Q_{t-1}, Q_t)$

Depending on the input vectors used, seven models were tested (Table 1). This technique allows taking into account the dynamics of the hydrological signal and learning this evolution. Initially, the model I was taken as a reference mode l (P_t, P_{t+1}, and Q_t), the number of membership functions (NMF) for ANFIS particular was set to two for each entry [13], thereafter, the NMF was varied up to six.

Gaussian membership functions are used for each fuzzy rule in the ANFIS system, this choice of functions is based on research work done by Gautan and Holz [14] and Lohani et al. [15].

Knowing that the membership functions have a significant influence on the performance of ANFIS models, the choice of model 1 was done to avoid the complexity of inference rules.

The results obtained for a NMF from two to six are summarized in Tables 2 and 3, respectively, for the basins of Turgot and Bordj Gobrini, where NMF represents the number of membership functions.

We find that the best performance for the basin Turgot is obtained for a NMF equal to two; this is same for all phases in the model I. Similarly, for the basin of Bordj Gobrini, we find that the best performance is obtained for a NMF equal to four for the testing phase. Now, we seek the best performance for the models shown in Table 1, depending on this membership functions.

In this capacity, Fig. 3 shows that the ASE is minimum for the model III for a NMF equal to two for the basin of Turgot. However, for the basin Bordj, Fig. 4 shows that the ASE is minimum for the model VI and this for a NMF equal to 4.

Performance parameters for the training phase, verification, and the testing phase for the two basins are given in Table 4. The comparison between the characteristics of the observed and simulated data by the ANFIS model for phases: training, validation, and test are summarized in Table 5.

The results show satisfactory results and good agreement between observed and calculated rates

Table 2
Parameters performance indicators of model I for Turgot basin according to the NMF

		Training phase			Verification phase			Testing phase		
Basin	NMF	ASE	CE	r	ASE	CE	r	ASE	CE	r
Turgot	2	*0.2932*	*0.9038*	*0.9508*	*3.8995*	*0.5031*	*0.7605*	*1.8123*	*0.6439*	*0.8126*
	3	0.6641	0.8845	0.8845	4.6135	0.4029	0.6925	2.3558	0.5371	0.7433
	4	0.5820	0.8092	0.8995	5.4552	0.2939	0.5899	2.6694	0.4755	0.6951
	5	0.5150	0.8311	0.9117	9.4476	−0.2228	0.7087	4.3413	0.1470	0.7372
	6	0.5759	0.8111	0.9006	7.0676	0.0853	0.2940	3.3566	0.3405	0.5837

Table 3
Parameters performance indicators of model I for Bordj Ghobrini basin according to the NMF

		Training phase			Verification phase			Testing phase		
Basin	NMF	ASE	CE	r	ASE	CE	r	ASE	CE	r
Bordj Gobrini	2	6.7987	0.7947	0.9313	9.0098	0.4588	0.6816	7.7458	0.7034	0.8642
	3	6.6023	0.8007	0.9347	8.2547	0.5041	0.7133	7.3101	0.7201	0.8694
	4	5.6349	0.8299	0.9515	8.2980	0.5015	0.7159	*6.7756*	*0.7405*	*0.8900*
	5	5.2048	0.8429	0.9589	9.5253	0.4278	0.6715	7.0555	0.7298	0.8684
	6	5.1857	0.8434	0.9593	9.7077	0.4168	0.6513	7.1227	0.7272	0.8809

Table 4
Parameters performance indicators of training, verification, and testing phases, to two membership functions for Turgot basin and to four membership functions for Bordj Ghobrini basin

		Training phase			Verification phase			Testing phase		
Basins	Models	ASE	CE	*r*	ASE	CE	*r*	ASE	CE	*r*
Turgot	III	0.1484	0.9514	0.9755	1.2841	0.8341	0.9156	0.6343	0.8755	0.9364
B. Ghobrini	VI	4.8687	0.8530	0.9647	8.3082	0.5030	0.7118	6.3381	0.7577	0.8956

Table 5
Comparison of flow characteristics observed and simulated by the ANFIS model for training, verification, and testing phases

Basins	Phases	Flows (m^3/s)	Mean	STD	Min	Max	C.V
Turgot	Training	Q. observed	1.086	1.747	0.2600	48.92	0.622
		Q. simulated	1.718	1.722	0.2470	48.92	0.620
	Validation	Q. observed	0.698	2.781	0.0100	75.71	0.251
		Q. simulated	0.650	2.433	0.0006	54.83	0.267
	Testing	Q. observed	0.920	2.256	0.0100	75.71	0.408
		Q. simulated	0.905	2.066	0.0006	54.83	0.438
Bordj Ghobrini	Training	Q. observed	1.53	5.757	0	91.9	0.266
		Q. simulated	1.144	3.554	1E-04	66.34	0.272
	Validation	Q. observed	1.091	4.084	0	42.3	0.267
		Q. simulated	0.857	2.85	0.001	44.45	0.302
	Testing	Q. observed	1.342	5.112	0	91.9	0.263
		Q. simulated	1.022	3.554	1E-04	66.34	0.288

Table 6
Results obtained by the models: MLR, of ANNs, and of ANFIS for the test phase

		Testing phase		
Basins	Models	ASE m^3/s	CE	*r*
Turgot	MLR	3.0000	0.4100	0.6400
	ANN	0.8205	0.7679	0.9162
	ANFIS	*0.6343*	*0.8755*	*0.9364*
Bordj Ghobrini	MLR	6.9800	0.7300	0.8600
	ANN	6.8867	0.7364	0.8583
	ANFIS	*6.3381*	*0.7577*	*0.8956*

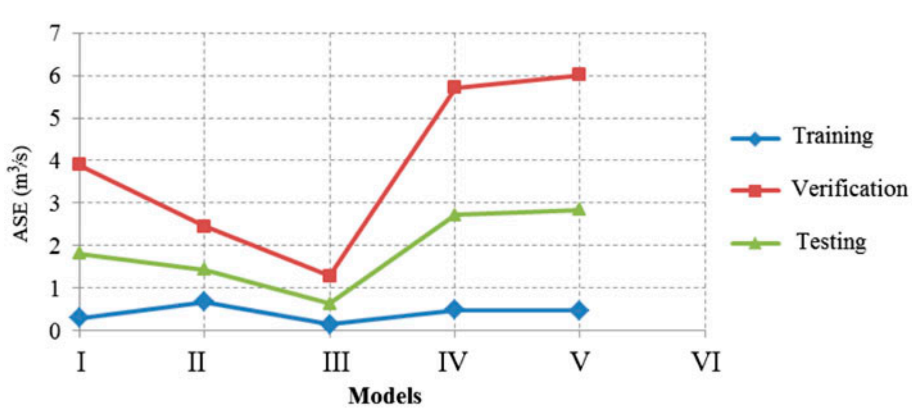

Fig. 3. Evaluation of the ASE for each model for a NMF equal to two (Turgot Basin).

explained by relatively high correlation coefficients for the test phase (Figs. 5 and 6). The best performances of the basin Turgot are mainly due to its small size, its compactness, and good representation of the rainfall station. For cons, the less satisfactory performances of the basin Bordj Ghobrini are probably related to the strong non-linearity of the rainfall–runoff relationship, the quality of data, and the location of measurement stations.

To evaluate the performance of the two models, we proceeded to calculate the Relative Error (RE) between the observed flows (Q_{obs}) and simulated flows (Q_{sim}).

Figs. 5(c) and 6(c) show that the RE is acceptable to the basin of Turgot, but it remains fairly high especially for extreme values for the basin of Bordj Ghobrini.

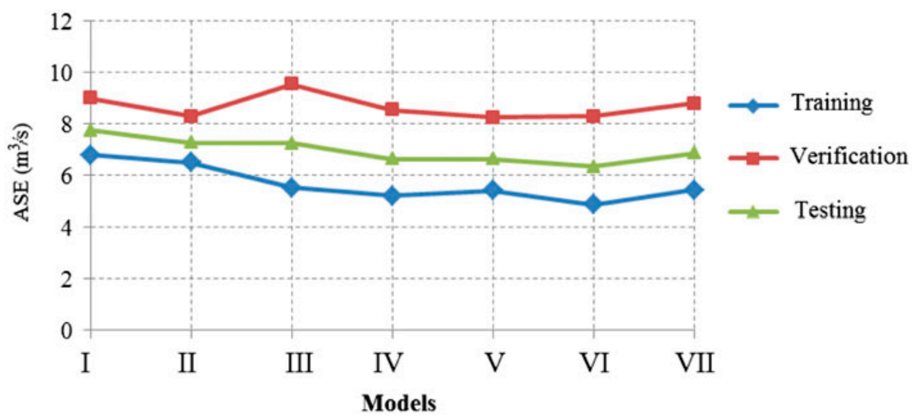

Fig. 4. Evaluation of the ASE for each model for a NMF equal to four (Bordj Ghobrini Basin).

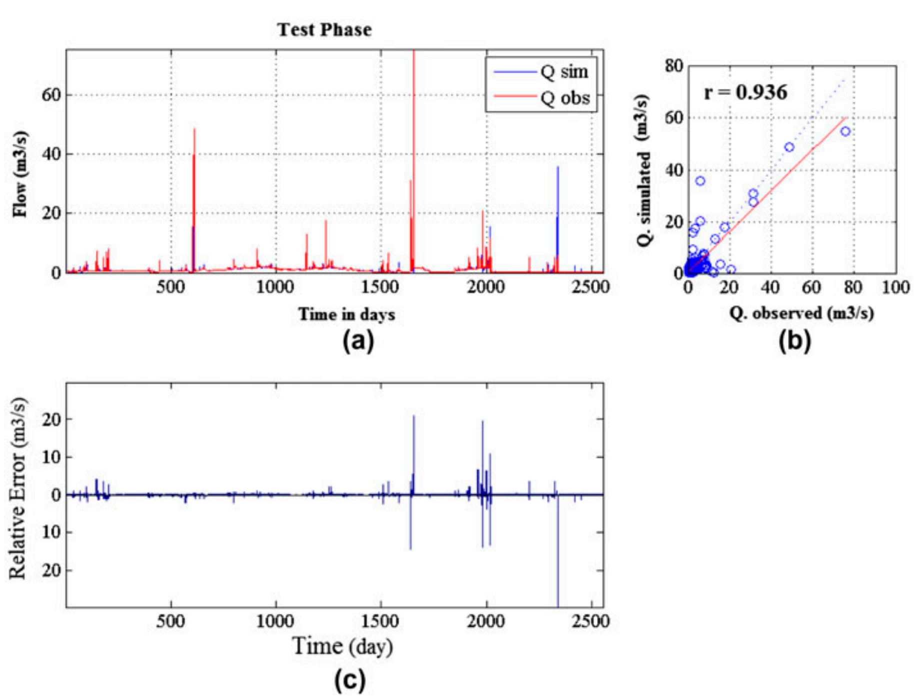

Fig. 5. Comparison between the observed flows and simulated flows (a, b) by ANFIS model and the RE between the observed flows and simulated flows and (c) for the test phase (Turgot Basin).

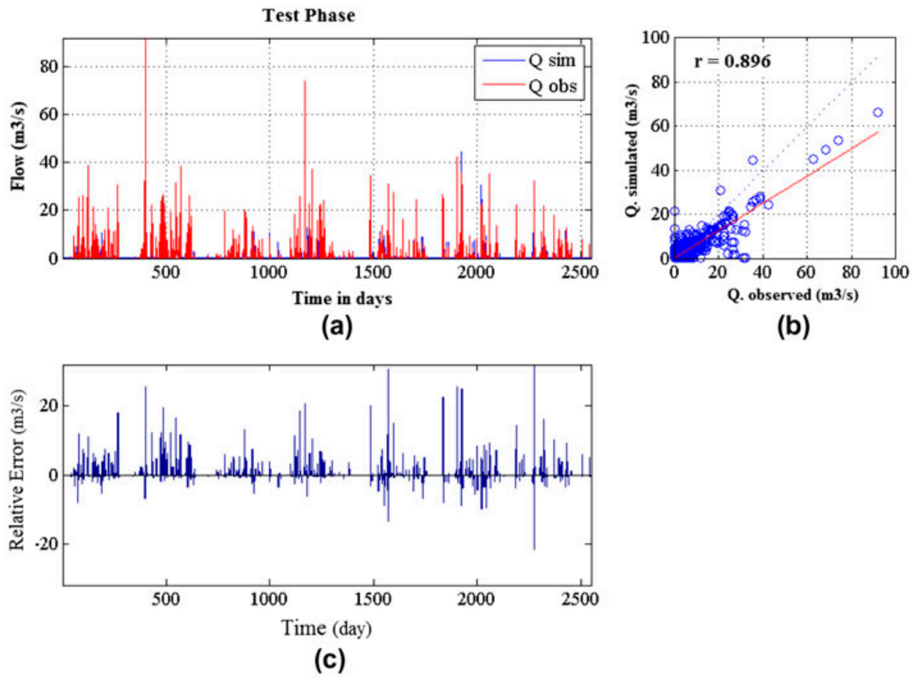

Fig. 6. Comparison between the observed flows and simulated flows (a, b) by ANFIS model and the RE between the observed flows and simulated flows and (c) for the test phase (Bordj Ghobrini Basin).

To evaluate the performance of the neuro-fuzzy model, a comparison was made with the classical model of Multiple Linear Regression (MLR) model and Artificial Neural Network (ANN) model. The application of these models was made on the same set of input data. Table 6 shows the results obtained by these three models.

These results show the performance of the neuro-fuzzy model that exceeds that of other models. This performance reflects the strength of ANFIS model and the accuracy of its outputs that allows it to give correct decisions and avoid situations of indecision.

5. Conclusion

The results obtained in this study showed the effectiveness of artificial intelligence algorithms for modeling the rainfall–runoff relationship for flow forecasting. neuro-fuzzy system has a good predictive power. The performance of ANFIS in hydrological forecasting exceeds those of other models. The use of this hybrid method is an alternative fully justified for good water management and especially to minimize the risk of flooding within the watershed. These encouraging results open a number of perspectives; it would be interesting to try hybrid models by coupling wavelet transform with neuro-fuzzy systems, and simultaneously optimizing by genetic algorithm: membership functions, scaling factors, and conclusions of fuzzy rules.

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