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Research Article

Calibrating Conceptual Rainfall Runoff Models using Artificial Intelligence

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Abstract

Rainfall runoff models are highly useful for water resources planning and development. In the present study, an effort has been made to develop three types of artificial intelligence techniques (genetic algorithms, fuzzy logic and artificial neural network) based rainfall runoff GR2M prediction model using current monthly rainfall, potential evapotranspiration and river basin area and give an output monthly runoff. The aim of this study is to evaluate the objective function between these three intelligence techniques in the Medjerda river basin, north east of Algeria. To do so, the mathematical model of GR2M is improved in MATLAB/Simulink and the proposed intelligence techniques are used. First, the offline GA setting is used to optimize the GR2M parameters. Second, technical intelligence, FL and ANN tuning online are used to consign to regulate by an adaptative control of the GR2M parameters. The GR2M model presented in our study with these proposed artificial intelligence techniques have been simulated in MATLAB/Simulink®. The performance of the model was evaluated qualitatively and quantitatively by visual observation and employing various statistical indices viz., correlation coefficient, root mean square error, coefficient of efficiency and volumetric error. The results showed that the neural network (ANN) is an effective algorithm to forecast rainfall runoff relation more accurately than the other techniques.

Key words: Conceptual models, GR2M, objective function, genetic algorithms, fuzzy logic, artificial neural networks

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Hydrological modeling is an important tool used in the management of water resources, especially in arid and semi-arid regions, where water resources are characterized by their scarcity and their erratic distributions in time and space. Models are also expected to provide useful information required in the design of hydraulic structures and the protection against floods. Models should accurately describe the various stages of rainfall runoff transformation, particularly the process related to flood formation and the emergence of low flows. Nevertheless, the complexity of the natural phenomena involved in the rainfall runoff transformation makes hydrological studies very complicated (Plantier, 2003). This complexity is further accentuated by the erratic spatial distribution of rainfall and watershed physiographic characteristics such as soil texture, relief and vegetation cover. It is almost impossible to model in an analytical fashion the different aspects of rainfall runoff transformation. Therefore conceptual lumped or distributed hydrological models are generally considered (Duan *et al*., 1992).

Conceptual models, such as the rural engineering model (GR) of Cemagref, are known to be robust, reliable and easy to use as they require limited data (rainfall, evapotranspiration and runoff series) for calibration, validation and simulation exercises. This type of model was shown to be quite useful in synthesizing the hydro-climatic information available in a watershed and in simulating its hydrological response (Kouassi *et al*., 2013).

The conceptual model used in this study is GR2M model, which is a two parameters model that transforms monthly precipitation data into monthly rainfall time series for a given watershed and under given conditions. The model is based on the analogy of two reservoirs for both production (soil infiltration) and routing or transfer function. Therefore, before its use, the model needs to be calibrated to determine appropriate parameters. For a given watershed, calibration exercise has to be conducted for parameters using similar conditions. This would imply that the pre-calibrated model needs to be used with caution if changes occur, for instance, in land use, vegetation cover, etc. (Mouelhi *et al*., 2006).

Traditionally, model calibration is performed by trial and error procedures, where different values are attributed to the model parameters X1 and X2 and simulation is performed. Then, simulated runoff series are compared to observed discharge data via statistical and graphical procedures. Simulations are then repeated until a reasonably good agreement between measured and simulated discharge time series is achieved. However, these procedure maybe lengthy and tedious and therefore alternative procedures are required. Indeed, calibration can be made systematic using artificial intelligence techniques (genetic algorithms, fuzzy logic and artificial neuron networks), which are becoming very powerful tools for the identification, optimization and control of the calibration parameters. Different studies applied genetic algorithm (Goldberg, 1989) for calibrating rainfall runoff models (Duan *et al*., 1993; Efstratiadis and Koutsoyiannis, 2002; Franchini and Galeati, 1997; Franchini, 1996; Franchini *et al*., 1998; Gupta *et al*., 1999; Thyer *et al*., 1999; Nasseri *et al*., 2011). Khazaei *et al*. (2014) presented an automatic calibration tool to calibrate the ARNO conceptual rainfall runoff model using a genetic algorithm (SGA). Babovic and Keijzer (2002) used genetic programming for creating rainfall runoff model and showed that the obtained models and had a better results than conceptual models.

Fuzzy Logic (FL), which represents a natural language resulting from the sets theory, was the subject of different studies such as, Bardossy and Duckstein (1995), Deka and Chandramouli (2003). Hundecha *et al*. (2001) employed fuzzy rule based routines to generate runoff from precipitation. The methodology was applied to conceptual, modular and semi-distributed model and proved FL to be effective. Pawar *et al*. (2013) reveals that fuzzy logic rule based model was found to be satisfactory on the basis of performance evaluation and can be applied for runoff prediction from study watershed.

Finally, the reliability of Artificial Neural Networks (ANN) in modeling non-linear phenomena was clearly shown in different scientific and engineering applications. In particular, its use was shown to be quite efficient in rainfall runoff modeling Elliott (1993), Coulibaly *et al*. (1999), Shamseldin *et al*. (2002, 2007) and Shrestha *et al*. (2005). Neuron models may directly relate rainfall to runoff, without going into details with respect to the involved hydrological process. This has the advantage of reducing the input data to a minimum (Randrianarivony *et al*., 2009).

Ali and Dechemi (2004) found artificial neural techniques to yield satisfactory results for the case of small watershed because of their underlying assumption of linear rainfall runoff relationship. Huang *et al*. (2004) simulated discharges in Apalachicola river (Floride, USA) using a feed-forward ANN model with reasonably good results at different time scales. A comprehensive review of ANN applications in hydrology can be found in the publication of the ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000). In addition, Shamseldin (1997), Kumar *et al*. (2005) and Mutlu *et al*. (2008) compared ANNs with different input variables for runoff simulation. The comparisons showed that the ANN models applying both with rainfall and discharge as input variables gave better results than the models with rainfall as the input. When the model utilizes of rainfall values as the input variables, the simulated hydrographs do not match the measured hydrographs so well (Halff *et al*., 1993; Filho and dos Santos, 2006). The results of Solaimani (2009) show clearly that the artificial neural networks are capable of model rainfall runoff relationship in the arid and semiarid regions in which the rainfall and runoff are very irregular, thus, confirming the general enhancement achieved by using neural networks in many other hydrological fields.

The current study is divided into three different parts, (1) Modeling and simulation using the conceptual model GR2M in MATLAB/Simulink interface, (2) Off-line optimization of the proposed model based on genetic algorithm and (3) On-line adaptation of the conceptual model parameters based on fuzzy logic and artificial neural network. The GR2M model is calibrated and applied to Medjerda sub-watershed, North-Eastern Algeria. The GA technique is first used and the calibration is then further refined using both FL and ANN technique. The results obtained are compared and the advantages of using both techniques in predicting discharges are discussed using the proposed case study.

MATERIALS AND METHODS

GR2M model into MATLAB: The available information is great importance to choice the hydrological model. In this information we have is the area of the basin and times series of rainfall and runoff. This oriented us towards lumped empiric hydrologic model that acts as input two of these are GR2M developed at the French CEMAGREF (Mouelhi *et al*., 2006).

Modeling has allowed us to present and simplify the equations to solve the model of our system in MATLAB/Simulink (Fig. 1), for this model we starting the point knowledge in this system is a production store whose capacity is the parameter x1 and actual content is S and a routing store whose capacity is set to 60 mm and actual content is R. The input variables according to the available data are monthly of rainfall (precipitation) (P), runoff monthly at the outlet of the basin (Q) and evaporation monthly (E).

A part Ps of rainfall P is directed to production store, whose content becomes S1. The excess part P1 is directed to the routing store. To take account of the evapotranspiration in the production store, a part S of E is extracted from this store. This new content of production store loses a quantity P2. The P2 is added to the routing store. Total water P3 input of the routing store and its content pass to R1. At this step, a fraction x2*R1 of R1 is reserved for the routing store and the difference is taken away from the basin as groundwater exchange. The level in the routing store becomes R2. Then the output runoff Q is estimated.

GR2M applied in genetic algorithms: Genetic Algorithms (GA) are computerized search and optimization tools based on a methodology inspired from the "Survival of Fittest" heuristic. One important feature in this heuristic is its durability and adaptability because it provides a flexible balance between effectiveness and necessary characteristics for survival in different environments and conditions (Johari *et al*., 2011). The optimization technique starts from a single point in the solution search space, then its search proceeds using a group of solutions representing the population of chromosomes at a time and navigates the search space using its three evolutionary methods; selection, crossover and mutation to reach the global optimum. The fitness function was used to evaluate the GR2M model calibration parameters (X1 and X2) of each generation. This function is the Integral of the Squared Error (ISE), for which the mathematical expression can be written as:

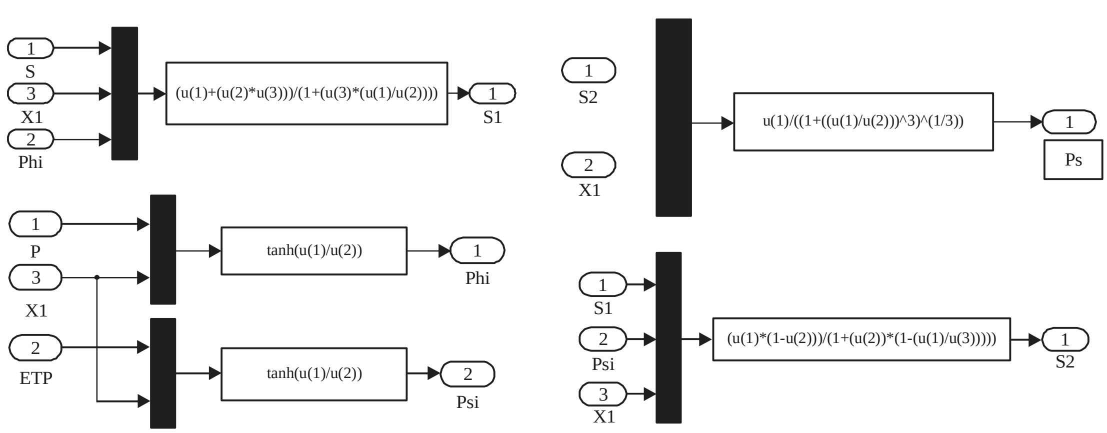

Fig. 1: Simulink MATLAB

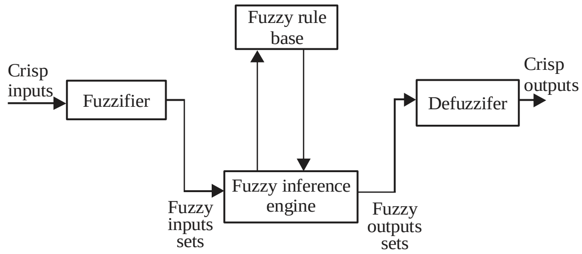

Fig. 2: Block diagram of a fuzzy logic system

Table 1: Rule list table of linguistic variables

	Outputs X1 and X2						
e/de	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NM	NM	NS	ZE
NM	NB	NB	NM	NM	NS	ZE	PS
NS	NB	NM	NM	NS	ZE	PS	PM
ZE	NM	NM	NS	ZE	PS	PM	PM
PS	NM	NS	ZE	PS	PM	PM	PB
PM	NS	ZE	PS	PM	PM	PB	PB
PB	ZE	PS	PM	PM	PB	PB	PB

NB: Negative big, NM: Negative medium, NS: Negative small, ZE: Zero, PS: Positive small, PM: Positive medium and PB: Positive big

$$ISE = \int_0^T \left|\varepsilon^2(t)\right| . \Delta t \tag{1}$$

where, $\varepsilon = Q_{obs}$-Q_{sim}, Q_{obs} is the observed discharge (m^3/sec) and Q_{sim} is the simulated discharge (m^3/sec).

The GA operators impose the quality solution, thereby increasing the probability of finding global optima, with minimum ISE values.

GR2M applied in fuzzy logic: A general fuzzy system has basically four components known as fuzzification, fuzzy rule base, fuzzy output engine and defuzzification (Fig. 2).

In the fuzzification interface, the fuzzy control initially converts the crisp error and its rate of change in displacement into fuzzy variables, which are mapped into linguistic labels. Membership Functions (MF) are defined within the normalized range [-1,1] and associated with each label as follow: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Negative Very Small (NVS), Zero (ZE), positive very small (NPS), Positive Small (PS), Positive Medium (PM) and Positive Big (PB). Seven MFs are chosen for error (e) and error rate (de) and two parameters for output. All the MFs are symmetrical for positive and negative values of the variables. Thus, maximum $7 \times 7 = 49$ rules can be formed as tabulated in Table 1 and the membership function used for the output of variables (X1 and X2) is presented in Fig. 3.

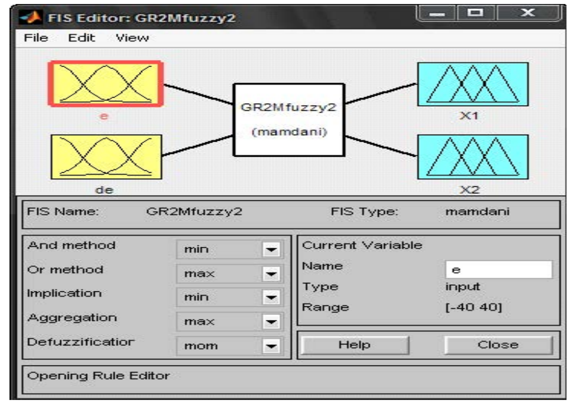

Fig. 3: Inputs and outputs of the fuzzy logic controller

The surface error and membership functions for the inputs (error and change of error) and output of fuzzy control are shown in Fig. 4(a-f). A knowledge base presented by a set of if-then rule, containing the definition of the fuzzy subsets is used to achieve good control. An inference mechanism is the heart of a fuzzy control, which performs the fuzzy reasoning upon the fuzzy control rules is the main component of the fuzzy controller. In this study the type of inference used is Mamadani. A defuzzification interface converts the conclusions of the inference mechanism into actual inputs for the process.

In this study, Center Of Area (COA) equation is used as a deffuzification method, which can be presented as:

$$C_g = \frac{\sum_{i=1}^{n} y_i X M_B(y_i)}{\sum_{i=1}^{n} M_B(y_i)} \tag{2}$$

where, C_g is the centroid of the truncated fuzzy output set B, $M_B(y_i)$ is the membership value of the element y_i in the fuzzy output of set B and n represent the number of elements.

Neural networks: Modeling of the GR2M with feed forward neural network is composed in this work. The scale of the input and output data is an important matter to consider, especially when the operating ranges of process parameters are different. As a result, all the input parameters are equally important in the training of network. The architecture of the designed network comprises two input neurons corresponding to two input parameters, an output layer with one neuron corresponding to one output parameter (Fig. 5). The transfer functions which have been used are tansig and purelin in hidden and output layers respectively. The transfer

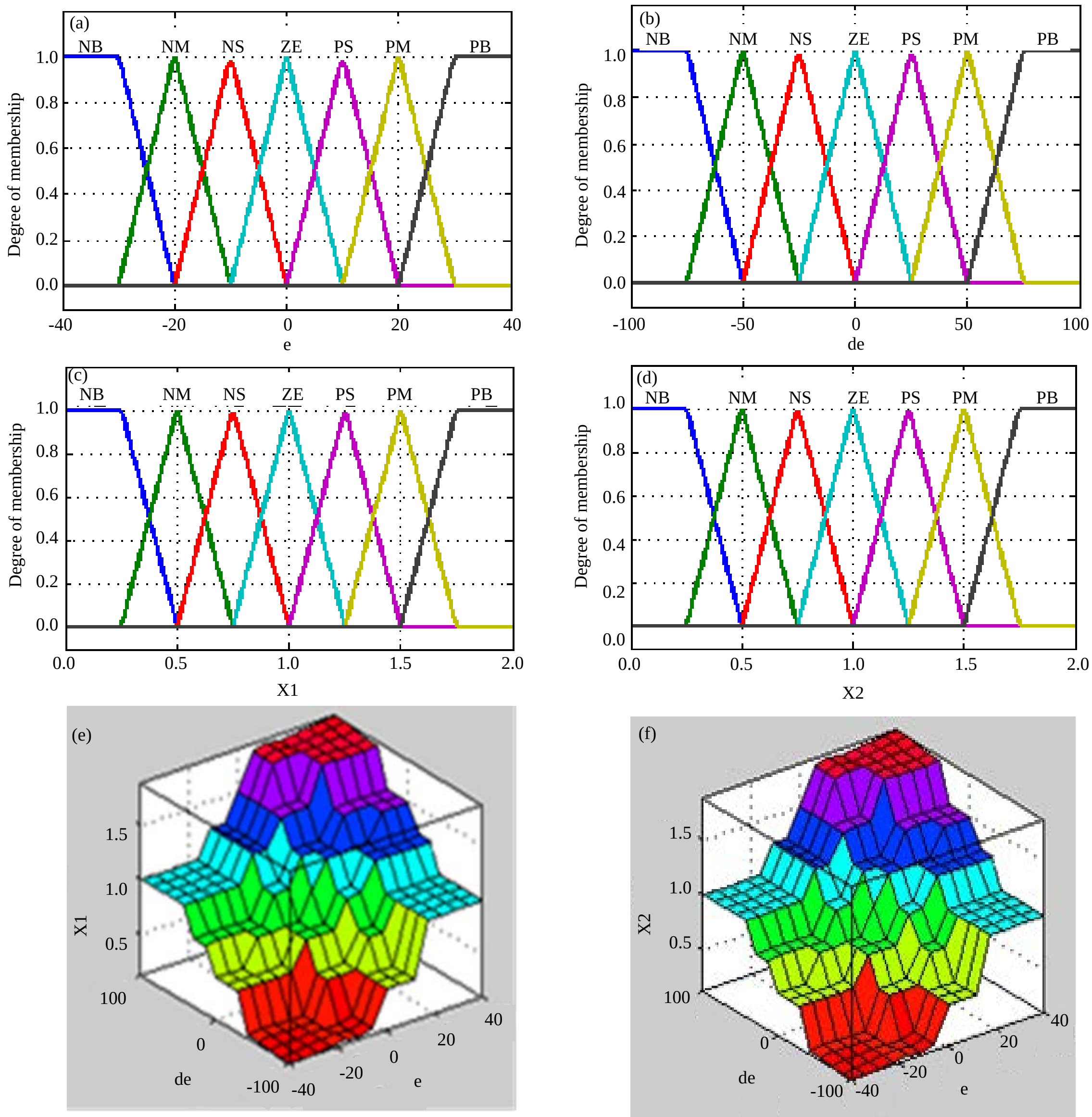

Fig. 4(a-f): Characteristics of GR2M fuzzy logic control, (a) Membership function "e", (b) Membership function "de", (c) Membership function "X1", (d) Membership function "X2", (e) Control surface "X1" and (f) Control surface "X2"

function tansig is a hyperbolic tangent sigmoid transfer function and purelin is a linear transfer function.

Study area and data used: The sub-watershed Medjerda is a one of the five component basins of Medjerda-Mellegue, which is situated in the southeast of Northern Algeria with a surface of 7870 km^2. The area of our study is located in the wilaya of Souk-Ahras between the 7°37' and 8°25' East meridians and the 36°05' and 36°27' Northern parallels. It is bordered by the coastal and Constantine basins to the north, algerotunisienne to the east, the Seybouse basin to the west and the Mellegue upstream and downstream basins to the south (Fig. 6). The climate of the Northern Algeria is influenced by the Mediterranean and is characterized by two types of seasons: the wet and cold season and the dry and hot season. The area of our study is typified by a semi-arid climate. The monthly average temperature varies between 5 and 30°C. The winter constitutes the cold period of the year with minimal monthly averages lower than 5°C. The summer, with maximum monthly averages higher than 30°C, is the hot period of the year. The prevalent wind directions are north-north-west in winter and north-east and south in summer. The air moisture of in the study area varies between 55 and 70% in the cold period (winter) and between 40 and

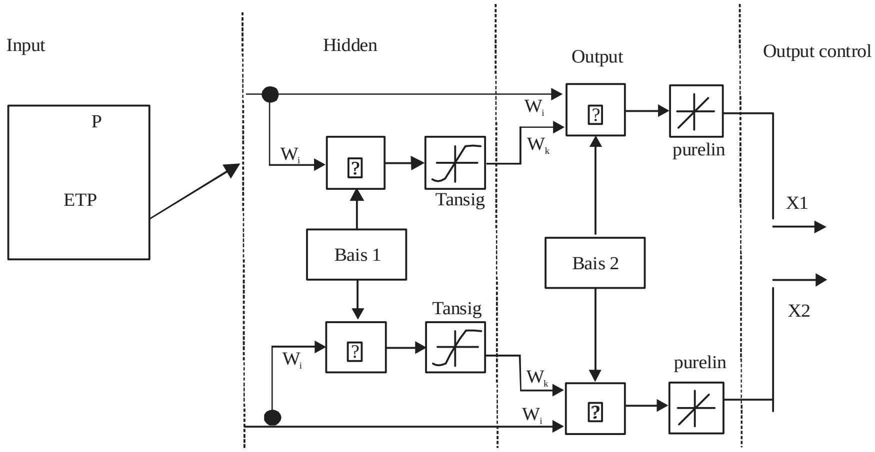

Fig. 5: Architecture of the designed network

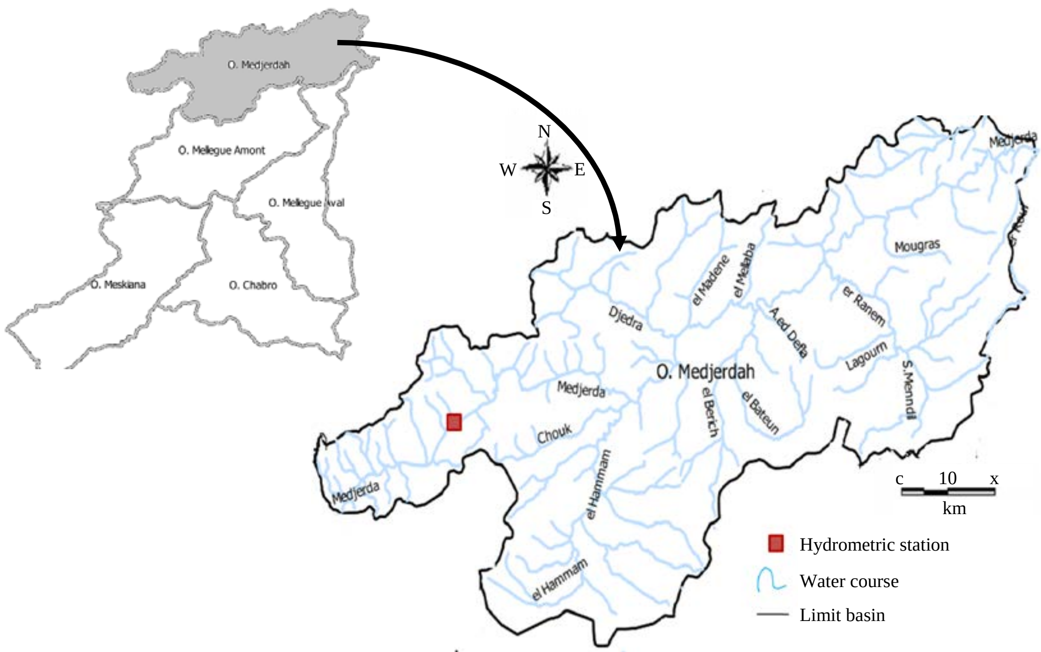

Fig. 6: Medjerda watershed

55% in the hot period (summer). The monthly potential evapotranspiration varies between 90 and 150 mm. Rainfall and discharge data were obtained from the National Agency of Hydraulic Resources (NAHR) and consist of monthly precipitation data of the Medjerda river basin from September, 1966 to December, 1995. The potential evapotranspiration (ETP in mm/month) is subject to the very strong variability in flow and precipitation; we assumed the monthly ETP to be quasi-constant from one year to another. In the Mediterranean climate of Algeria, the real evapotranspiration is largely determined not by the ETP, but by the available water as well the rain. Thus, in the context of this study, the ETP was a corrective term and the monthly average potential evapotranspiration will be enough to correctly represent the ETP for each month (Dechemi *et al*., 2007). To validate the model, we use hydrometric and rainfall data with a period of observation from September, 1965 to December, 1995.

RESULTS AND DISCUSSION

To examine the ability of the real GA to optimize the parameters of our model, different crossover and mutation rates are used. Ten runs were used with different initial seeds resulting in different initial starting populations of points and

Table 2: The results of 10 running's of the genetic algorithm

Running	X1	X2	ISE
1	0.8517	0.9874	13.4129
2	0.7143	1.6236	9.8105
3	0.7638	1.7638	4.6946
4	0.9794	0.9794	7.0686
5	1.0463	0.8695	9.1105
6	0.9876	1.1228	6.7087
7	0.6232	0.799	4.9885
8	0.7754	0.8754	0.797
9	1.1585	0.9228	4.9183
10	0.9751	0.6751	3.3184

ISE: Integral square of error

Table 3: Statistical indices-comparison between three intelligence techniques

Running	GA	FL	ANN
Coefficient of correlation (R)	0.98	0.98	0.99
Coefficient of efficiency (E)	0.98	0.94	0.99
Root-Mean-Square Error (RMSE)	0.765	0.763	0.0012

GA: Genetic algorithms, FL: Fuzzy logic, ANN: Artificial neural network

different operations. Table 2 shows the best points found in each of the 10 runs and X1, X2 and ISE. Set of parameters corresponding to the smallest ISE values are then considered as models parameters.

The research in the Table 2 show that all ten optimization runs proved to be able to locate the global optima for X1 and X2. In some runs, the search landed at a local optimum. This happened only when the objective function value of the local optimum was similar to that of the global optimum. In term of minimizing the objective function, the GA has shown to be both capable and robust for the eight run's with ISE = 0.80. Cooper *et al*. (1997) show that the GA use probabilistic transition rules, not deterministic ones and they are generally more straight forward to apply and can provide a number of potential solutions to a given problem. This study was conducted to control the parameters (x1 and x2) with FL and ANN model for Medjerda station (Souk-Ahras).

Various simulations were carried out by using MATLAB/Simulink to assess the performance of the integrator with a fuzzy controller on the feedback. The fuzzy controller used for estimating the parameters was developed with the MATLAB fuzzy toolbox. Simulations were performed to investigate transient state and steady state performance of the proposed parameters estimator. In this way, the performance of the proposed model was analyzed by means of a variety of statistical criteria coefficient of correlation (R), coefficient of efficiency (E), Root-Mean Square Error (RMSE) between the calculated and computed flow values. Although it is commonly accepted that the lower the RMSE the better the model performance, Singh *et al*. (2005) have detailed the indication RMSE based on the observations standard deviation.

The statistics of the above criteria for different techniques is presented in Table 3.

$$E = 1 - \frac{\sum_{i=1}^{n}(Q_{observed}(i) - Q_{predicted}(i))^2}{\sum_{i=1}^{n}(Q_{observed}(i) - \overline{Q_{observed}})^2} \quad (3)$$

Where, n is number of data point:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_{observed}(i) - Q_{predicted}(i))^2}{n}} \quad (4)$$

$$R = \left[\frac{\sum_{i=1}^{n}(Q_{observed}(i) - \overline{Q_{observed}(i)})(Q_{predicted}(i) - \overline{Q_{predicted}(i)})}{\sqrt{\sum(Q_{observed}(i) - \overline{Q_{observed}(i)})^2 \sum_{i=1}^{n}(Q_{predicted}(i) - \overline{Q_{predicted}(i)})^2}}\right] \quad (5)$$

It is observed from the Table 3 that performance of both the models in terms of statistical indices is very similar and satisfactory. The higher values of correlation coefficient for control as well as different model show good agreement between observed and predicted values of runoff. While evaluating capability of the model for predicting runoff values away from the mean, efficiency of both the models is found to be greater than 90%, which according to Shamseldin (1997) is very reasonable. Lesser value of RMSE indicates the model performance is comparatively better to predict the parameters X1 and X2. Hence, the comparative performance of the run off results by applying physical checks in Fig. 7. All models show good agreement with experimental results. When compared the intelligence techniques, the ANN model has shown a significant forecast improvement than the model FL as 3 and 13% for GA. For the flow dynamics (Fig. 7), there is a good reproduction of observed and calculated hydrographs are indeed very well synchronized with the months appear floods and low flows. But, there are some differences between these hydrographs for GA particularly at extreme speeds and fails to adequately simulate the lower flow peaks. Besides being more efficient, neural networks are also more economical than the FL and GA technique. Indeed, with only two parameters (X1 and X2) as input, the neural patterns appear more powerful and satisfying; the modeler spends less with neural models with other artificial intelligence. It would be cheaper to use neural models that require more variables.

The quantitative performance of the model was also assessed by another measure i.e., volumetric error and is given

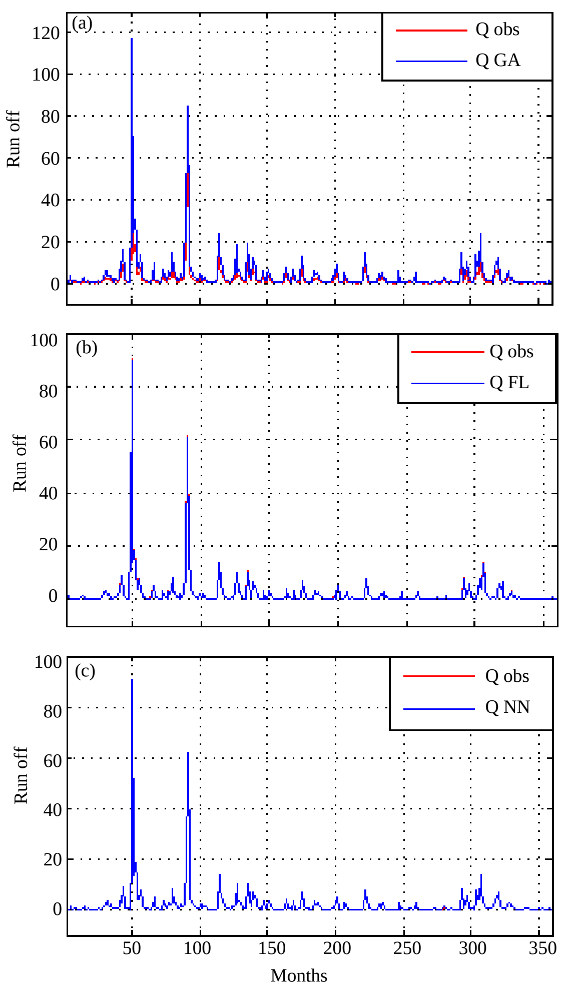

Fig. 7(a-c): Simulated and observed runoff

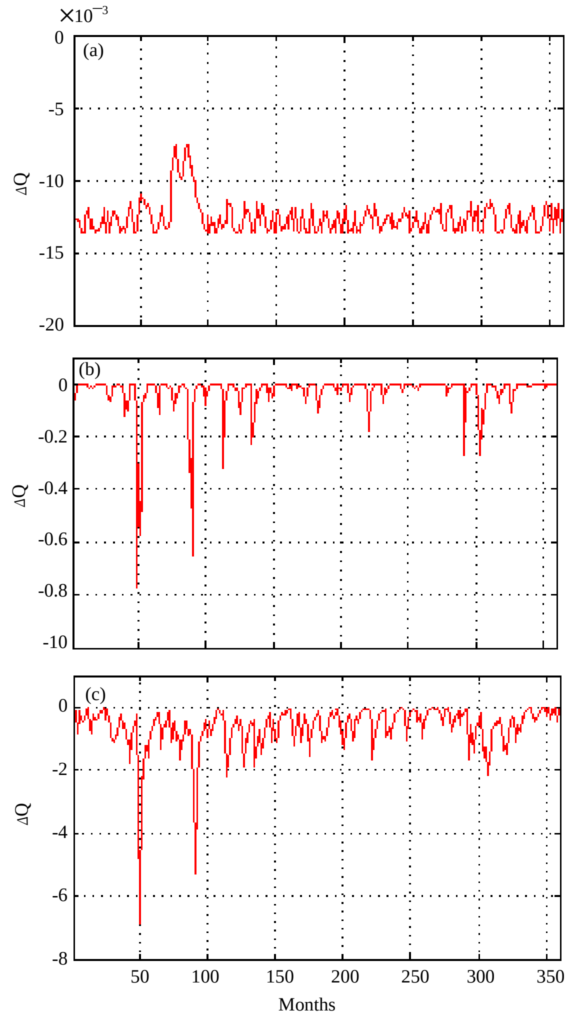

Fig. 8(a-c): Error between simulated and observed runoff

in Fig. 8. Using the AI based model, the values of volumetric error of study watershed for control period are 0.298% for GA, 0.772% for FL and 0.628% ANN, respectively.

The comparison of the computing time constitutes one of the justifying shutters of simulation. From the starting assumptions, several reasons could explain a marked improvement of computing time. The artificial intelligences are very difficult executions which subdivide the step of time instep of smaller internal times. The number and the size of the internal subdivisions not being known in advance, inside a step of time and of a step of time to the other, it remains always difficult to quantify the total duration of the execution of AI in advance which depends on the conditions of convergence met during the execution and other factors. It is indeed necessary to take account of the execution time of instructions of the system necessary to the execution of the program. This last time depends on the load of the system due in particular to the other programs in the course of execution. The execution times are then measured in both cases and the same conditions for implementation.

Thus, according to Table 4 we reach the following conclusions:

- To use the GA, the parameters of GR2 M model are fixed. The ISE is large but acceptable; ISE is high during tuning and low during drive operation and has a minimum settling time for the fixed parameters of the GR2 M model as well as a low cost
- To use the FL, the parameters of the GR2 M model are variable, the ISE is medium and a good starting transient performance also provides a medium settling time and a medium cost as a result of the design of the circuit in fuzzy logic
- To use the ANN, the parameters of the GR2 M model are variables, including a small ISE and a very good starting transient performance also provides a large settling time

Table 4: Comparison among intelligence techniques

Parameter	ISE	Settling time (sec)	Starting transient performance	Computational effort
GA	0.797	65	Good	High during tuning and low during drive operation
FL	0.01	409	Good	High
ANN	0	5894	Very good	High

GA: Genetic algorithms, FL: Fuzzy logic, ANN: Artificial neural network and ISE: Integral square of error

and a high cost as a result of the design of the circuit in the artificial neural networks with a complexity in the phase of implementation

The summary of results for the three AI approaches used in this study, that all model simulate very well the flow of the station Medjerda watershed. But ANN has been a preferred choice among the various soft computing techniques for modeling rainfall runoff phenomenon. Indeed, control of optimization parameters (X1 and X2) to the GR2M model, CE obtained is very important and higher compared to the other two (GA and FL) and the correlation coefficient R is greater than 0.90 reflecting the strong correlation between the measured flow rates and those calculated by the ANN.

Comparing the results obtained in this study with those of some authors, we note that the results here are different from those obtained by Ali (2006) with a neural network, Nash criteria was obtained by this study is 60%. This results is due to the structure of the model developed here which is directed as a result of the introduction of the flows measured at the preceding time as an additional input of the neural network. The study of De Vos and Rientjes (2007) shows that performance of RNA is superior than HBV model for objective functions on low flows and floods but less for a new objective function including the shape of the hydrograph. If the forecast time increases, the HBV model is superior to the RNA for all objective functions. Also, the comparison of the performance model between ANN and FL to predict the stream flow modeling of Savitri Basin (Kothari and Gharde, 2015) prove that ANN model performance is quite superior.

In another side, Lohani *et al*. (2011) compares Artificial Neural Network (ANN), Fuzzy Logic (FL) and Linear Transfer Function (LTF)-based approaches for daily rainfall runoff modeling. This study applied the potential of Takagi Sugeno (TS) fuzzy model and the impact of antecedent soil moisture conditions in the performance of the daily rainfall runoff models. The results show that the fuzzy modeling approach is uniformly outperforming the LTF and also always superior to the ANN-based models.

CONCLUSION

In this way the proposed model can find the appropriate (X1 and X2) are the coefficient of the GR2M model for rainfall runoff process. Artificial Intelligence (AI) techniques such as neural networks, fuzzy logic and genetic algorithms are applied in the normal operating conditions. The obtained simulation results of adaptive structures (fuzzy logic and artificial neural networks) show more robustness against the GR2M parameters as well as high disturbance rejection capability compared to the fixed structure technique (genetic algorithm) and the ANN technique is more superior overall. All models show good agreement with experimental results. When compared to the ANN and FL models, the ANN model has shown a significant forecast improvement. The results indicate that the ANN model is an effective algorithm to forecast the parameters of R-R. In addition, this study presents technical and commercial index performances composed of the Integral of Squared Error (ISE), settling time and starting transient performance. The computational effort and the cost of implementation for using these intelligence approaches are considered in tuning the GR2M parameters.

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