Performance Evaluation of Multilayer Perceptron Neural Network and Adaptive Neuro-Fuzzy Inference Systems for Reservoir Operation Optimization: a Case Study of Cheffia Reservoir, Algeria

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Abstract− Artificial Intelligence based prediction has wide applications, including hydrology, water resources management and particularly reservoir operation. Thus, two black box models based on Artificial Neural Networks and Fuzzy Logic methods are implemented and tested in forecasting reservoir operation; the first is a Multilayer Perceptron Neural Network and the second is an Adaptive Neuro-Fuzzy Inference System combining the two methods. The developed models consist of predicting evaporation, inflows and reservoir storage from their historical records and that, with aim of providing the best fit between predicted and observed values and of improving operating rules on storage and releases. The performance of achieved results demonstrated the pertinence of Artificial Neural Networks and fuzzy Logic methods in predicting cyclical state variables, such as evaporation and storage, while the prediction of inflows to reservoir generally gave better results compared to other research works available in open literature on one hand. On other hand, it is deduced from testing different prediction models that these methods are unable to predict random variables.

***Keywords*− Modelling, Prediction, Reservoir, Inflow, Artificial Neural Networks, Fuzzy logic.**

NOMENCLATURE

ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
CANFIS	Co-Active Neurofuzzy Inference System
CC	Correlation Coefficient
DENFIS System	Dynamic Evolving Neural-Fuzzy Inference
LR	Learning Rate
MAE	Mean Average Error
MCM	Million Cubic Meter
MLPNN	Multilayer Perceptron Neural Network
NC	Nash Coefficient
NN	Neurons Number
RMSE	Root Mean Square Error
RN	Rules Number

I. INTRODUCTION

Water is a vital natural resource. Though it is renewable, it is quantitatively limited and its distribution is stochastic in a semiarid regions. It can be stored in dam reservoirs during wet periods of precipitations for satisfying water demand during low water periods, that why reservoir releases regularization remains a difficult task in the conditions of uneven spatiotemporal distribution of rainfalls accentuated by the climate change. Reservoirs operation is subject to operating rules associated with plant objectives that impose a minimal or maximal bound on the total flow able to be released from reservoir. These operating rules are considered as function of inflows, reservoir storage and releases.

Generally, operating inflows, as a state random variable, is a difficult task. Particularly when they are overexploited or underexploited for making decision about releases, whose estimation and allocation between users constitutes the objective of reservoir system exploitation and that, through taken options at the beginning of each decision period for satisfying as far as possible target objectives imposed to reservoir system. Depending on inflows, the reservoir releases are conditional on the storage and they are determined simply to satisfy water demand and to meet their target storage by insuring minimum flow requirements. Their systematic evaluation is subject to uncertainties. With aim of reducing the uncertainty and improving reservoir operation, different models exist for describing and analyzing the behavior of reservoir releases operation through the assessment of various scenarios. Several tools are used in matter of reservoir operation modelling; from dynamic programming to linear and nonlinear programming, to stochastic dynamic programming and to artificial intelligence with artificial neural networks (ANN) and fuzzy logics that emerged as viable tools for reservoir operation modelling and forecasting (Labadie, 2004) [1]. Likewise, multiple models based on fuzzy logics have been carried out in hydrology and water resources management. Recently, Panigraphi and Mujumdar (2000) [2] attempted to provide an implementable single purpose reservoir operation policy, using fuzzy logic methods. They found that the latter might remain limited to a single reservoir operation, because of the curse of dimensionality that is observed in a fuzzy rule based model. As the number of fuzzy sets increases, the dimensionality of the problem grows multiplicatively. What has been pointed out by Russell and Campbell (1996) [3] and it implies that the fuzzy

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logic approach is not an alternative to the more conventional optimization techniques.

Adaptive NeuroFuzzy Inference System (ANFIS) method, merging ANN and fuzzy logics, has been used for reservoir operation forecasting. For instance, Chang and Chang (2001) [4] combine Genetic Algorithms (GA) and ANFIS methods for determining the optimal real time reservoir release operation. Learning from the input-output patterns obtained from GA, they estimate the reservoir release in predefined conditions using ANFIS model. First, their work consists of using the subtractive fuzzy clustering to reduce the number of input rules; as the number of variables increases, the number of parameters of membership functions increases highly. As to the second problem, the objective function does not express the reservoir operation characteristics. Several optimal solutions have the same minimum value in the objective function of reservoir operation. From another side, El Shafie and all (2006) [5] developed an ANFIS model with a high accuracy in forecasting average inflow events of the Nile River at Aswan High Dam, especially for extreme events, given a high uncertainty in future inflows, making of developing optimal release policies of a multi-purpose reservoir a complex process. On the contrary, Chang and all (2014) [6] explored the effectiveness of multiple sources of rainfall characterized by a complex temporal heterogeneity, and they found if the ANFIS model is fed with the assimilated precipitation, it provided reliable and precise rainfall forecasts and can be a great help on floods warnings. On the other hand, a neuronal model based on the radial function using inflows and releases as inputs for predicting water losses, might give better results, depending generally on the data size and the neural model parameters (Samad and all, 2015) [7]. In the same field of reservoir operation modeling, Kisi and al (2017) [8] demonstrated the accuracy of the dynamic evolving neural-fuzzy inference system (DENFIS) in modeling pan evaporation compared with the classic ANFIS model. The latter differs from DENFIS new model by using an evolving clustering method, a triangular membership functions as fuzzy sets and an alternative weighting scheme for local learning of consequent parameters. Salih and all (2019) [9] applied ANFIS and Co-Active Neurofuzzy Inference System (CANFIS) models successfully in predicting monthly reservoir evaporation; a good accuracy is reached using only two inputs of air temperature and relative humidity. Alquraish and al (2021) [10] in predicting inflows to reservoir, succeeded in improving the forecasting performance of ANFIS model using an add-in optimization algorithm based Genetic Algorithms methods. In the present case of Cheffia reservoir, a performance evaluation of artificial neural networks and fuzzy logic methods is made in predicting evaporation, inflows and reservoir storage in order to define appropriate operating rules on releases.

II. Material and Methods

1. Study Area

Cheffia dam reservoir (Fig.1) is set up on Bounamoussa River, situated in the Northern East of Algeria. Watershed reservoir covers an area of 575 km^2 and received an average monthly rainfall of 61 mm with a standard deviation of 70 mm. Reservoir is intended to satisfy agricultural needs in water through releases modulated from spring to autumn and reinforced in a summer for the irrigation, and likewise to supply the region in drinking water. Reservoir storage is 180,8 MCM. Observed data covers the period of forty years and are collected from the reservoir operating budget (1979-2019). Five variables are assumed as input state variables, namely reservoir storage, inflows to reservoir, evaporation and seepage, and one as an output decision variable, namely releases. The maximum and the minimum of the reservoir storage are 202 MCM and 30 MCM corresponding respectively to the forced storage volume and reservoir dead volume or ecological volume. By the monthly inter annual average, the water consumption and evaporation represent respectively and nearly 59% and 12% of the inflows.

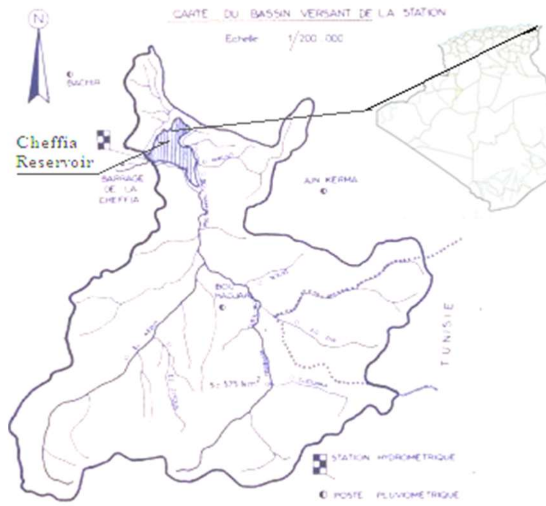

Fig.1: Map of Cheffia Reservoir and its watershed

The operating mass balance of Cheffia reservoir is derived from a continuity equation as:

$$S(t+1) = S(t) + I(t) - E(t) - WC(t) - SEEP(t) \text{ (MCM)} \quad (1)$$

Where *S(t+1)* is storage at time step *t+1* ; *S(t)* is storage at time step t ; *I(t)* is inflow at time step t ; *E(t)* is evaporation at time step t ; WC(t) is water consumption at time step t and $SEEP$(t) is water seepage.

The permissible water storage is given as: $S_{min} \leq S(t) \leq S_{max}$

Through the continuity equation of the operating mass balance, the natural processes such as inflows and evaporation are the preponderant inputs to the system; they are uncertain events estimated systematically. Furthermore, the releases are conditional on the storage that depends on the inflows characterized by the randomness.

2. Architecture of MLPNN model

The objective of prediction consist in providing manager a decision making tool for a rational water management. Thus, the adopted MLPNN model is a conventional feedforward neural network with three layers (Rumelhart and all, 1986) [11].

The supervised learning is implemented iteratively; at each iteration, the synapses weights and the networks bias are modified using the gradient descent method, a criteria in minimizing the quadratic error is defined as the gap between the observed and the predicted activated functions, expressed as follows:

$$E = \frac{1}{2}\sum_{i=1}^{n}(y_i - \acute{y}_i)^2 \quad (2)$$

Equation (2) is the reduced form of the mean squared error E or usual function minimized in least squares regression and where n is the patterns size, y_i represents the observed activated function of output neuron i and $\hat{y}_i$ is the predicted activation function of that neuron. Once a network converges to a solution, it is then able of classifying each unknown input pattern with other patterns that are close to it in terms of the same distinguishing features. From the mathematical point of view, MLPNN may be considered a multivariate nonlinear nonparametric statistical method (White, 1989, Ripley, 1993) [12] [13]. A typical MLPNN with five hidden layers containing M neurons is based on the following equation:

$$\acute{y}_i = f\left(\sum_{i=1}^{n} w_{ij}x_i + e_j\right) \quad (3)$$

Where $\acute{y}_i$ is the output value of the neuron, expressed as a function f of the sum of the weighted inputs of the hidden neurone j and the relating bias. N is the total number of input neurones, w_{ij} is the weight from input neurone i to the hidden neurone j, x_i is a value of the ith pattern input and e_j is the bias (or threshold) for neuron j.

3. Architecture of ANFIS model

An adaptive network, as its name implies, is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, parts or all nodes are adaptive, which means each output of these nodes depends on the parameters belonging to this node and the learning rule specifies how these parameters should be changed to minimize a prescribed systematic error. ANFIS is a multilayer feed-forward network where each node performs a particular function on incoming signals. Both square and circle node symbols are used to represent different properties of adaptive learning. To perform desired input–output characteristics, adaptive learning parameters are updated based on gradient learning rules (Jang, 1993) [5]. For simplicity, we assume the fuzzy inference system under consideration has two inputs, *x* and *y*, and one output *z*.

Suppose that the rule base involves two fuzzy if–then rules of Takagi and Sugeno's type:

$$Rule1 = If\ (x\ is\ A_1)\ and\ (y\ is\ B_1)\ Then\ (f_1 = p_1x + q_1y + r_1) \quad (4)$$

$$Rule1 = If\ (x\ is\ A_2)\ and\ (y\ is\ B_2)\ Then\ (f_2 = p_2x + q_2y + r_2) \quad (5)$$

Where *x* and *y* are inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Fig.2, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

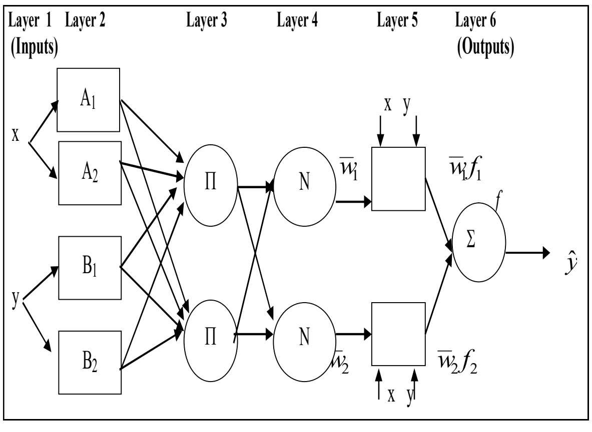

Fig.2: ANFIS Model

Layer 1: this layer transmits data inputs to the fuzzification layer.

Layer 2: Each node of this layer is a square node with a function expressed by:

$$O_i^2 = \mu_{A_i}(x) \quad (6)$$

Where x is input to node i, and Ai is the linguistic state associated with its function, in others words, O_i^2 is the pertaining degree of x to Ai in Jang model; membership functions are Gaussian.

Layer 3: Each node *i* in this layer is a circular node labelled *Π* that induces as outputs the product of its inputs; this product represents the activation degree of a rule expressed by:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad (7)$$

In others words, each node of this layer corresponds to a Sugeno fuzzy rule; it receives neurons outputs of fuzzification and computes its activation.

Layer 4: In this layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized activation degree of a rule *i* given by:

$$O_i^3 = \overline{w}_i f_i = \left(\frac{w_i}{(w_1 + w_2)}\right) \quad (8)$$

Layer 5: each node in this layer is a square node with a function given by:

$$O_i^5 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad (9)$$

Where $\overline{w}_i$ is the output of Layer 3 and ({p_i, q_i, r_i}), called consequent parameters, are the output parameters set of this node (Jang, 1993) [14]. Each neuron *i* of this layer is relied with a corresponding normalization neuron and to initial network inputs.

Layer 6: the single node of this layer is a circular node that sums the node's outputs in the previous layer to be the outputs of the whole network given by:

$$O_i^6 = \sum_{i=1} \overline{w}_i f_i \quad (10)$$

The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters using a standard backpropagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS (Jang, 1993)[14].

4. Performance Metrics For Models Calibration and Validation

a. *Correlation coefficient*

$$CC = \frac{\sigma_{xy}}{\sigma_x * \sigma_y} \quad (11)$$

Where σ_x: is the standard deviation of the observed values ;
σ_y: is the standard deviation of the predicted values;
σ_{xy}: is the standard deviation of the observed and predicted values. $-1 \leq CC \leq 1$

b. *Root Mean Square Error*

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - y_i\right)^2} \quad (12)$$

When RMSE converges to zero represents the perfect fit

c. Mean Average Error

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|x_i-y_i\right| \quad (13)$$

Others metrics are important for testing or validating the model, they're as follows:

d. Nash Coefficient(NC)

It is expressed as follows:

$$NC=\left[1-\frac{\sum_i^n (x_i-\hat{y}_i)^2}{\sum_i^n (x_i-\bar{y})^2}\right]*100 \quad (14)$$

x_i: Observed values;
$\hat{y}_i$: Predicted values;
$\bar{x}$: Average of observed values.
This metric is first used for deeming a model operating by episodes (Nash and al, O'Connel et. al, 1970) [15] [16]. It expresses the variance percentage of the measured series, explained by the model.

e. The Biased Average

The biased average is the difference between the averages of the observed and the predicted values (Legates and all, 1999) [17] given as follows:

$$\{B\}=\bar{y}_i-\bar{x}_i \quad (15)$$

$\bar{y}_i$: Average of predicted values;
$\bar{x}_i$: Average of observed values.
When $\{B\}$ converges to zero, the averages coincide.

f. Variation index

The validation of the used model may be completed by comparing the variation coefficients of the observed and the predicted values.

$$I=\frac{Cv_y}{Cv_x} \quad (16)$$

Cv_y: Variation coefficient of the predicted values;
Cv_x: Variation coefficient of the observed values.
If the variation index I is near to unity, the prediction is perfect.

III. RESULTS DISCUSSION

The reservoir operation efficiency depends on the decision making on releases through reservoir operating rules, developed from an accurate knowledge of preponderant state variables, such as evaporation, inflows to reservoir and storage, which they should be closely linked. For assessing the prediction model of these parameters, the period of the model testing or validation is three years (2015-2018). The adopted model is assessed according to neurons number, lag time, learning rate and validation. The prediction of state variables is expressed by the following equation:

$$X_t=a_0+a_1X_{t-1}+a_1X_{t-2}+a_1X_{t-3}+a_1X_{t-4}+a_1X_{t-5}+a_1X_{t-6} \quad (17)$$

Where X_t : predicted values at time t with a lag time of t-2, t-4 and t-6.
t : Time step (month), $a_0, a_1, ... a_6$: Coefficients.
The adopted neural model « MLPNN » has four options of the neurons number (NN) corresponding to five, ten, twenty and one hundred, respectively, the lag time is t-2, t-4 and t-6 and a learning rate (LR) is varying from 10% to 90%. As to ANFIS model; it includes three options corresponding to a rules number (RN = 2), a learning rate (LR= [10%: 90%]) and a lag time (t-2 ….t-6).

1. Evaporation prediction

Such as a cyclical preponderant variable acting on storage; its significance increases from a semiarid climate to arid. In the case of Cheffia reservoir situated in the semiarid region, by a monthly inter annual average, it is 0,579 MMC representing 12% of inflows to reservoir.

The achieved predicted values are better given the remarkable performance metrics whether in a calibration or validation phase (Table.I); the best model MLPNN which gives the best predicted values is the third model (Model-3) with a neurons number, a learning rate and a lag time equal to 5, 90% and t-4, respectively.

Thus, the model validation has given the best correlation between observed and predicted values of evaporation, whose CC, RMSE, MSE, NC, biased average {B} and variation index (I) are 0,990, 0,003, 0,001, 89%, 0,27 and 1, respectively. Fig.3, 4 and 5 show the best fit between observed and predicted evaporation values.

Table I
Performance metrics of the evaporation prediction using **MLPNN** model. (**C**: Calibration, **V**: Validation)

		Lag time	NN	LR %	CC	RMSE	MSE	NC	{B}	I
Model -1	C	t-2	5	50	0,815	0,016	0,011			
		t-2	10	50	0,805	0,021	0,026			
		t-2	10	50	0,740	0,020	0,019			
	V	t-2	5	50	0,926	0,012	0,021	83%	0,031	1,007
		t-2	10	50	0,901	0,001	0,001	80%	0,027	0,988
		t-2	10	50	0,943	0,003	0,002	88%	0,021	1,040
Model -2	C	t-4	5	50	0,889	0,013	0,004			
		t-4	10	50	0,894	0,015	0,016			
		t-4	20	50	0,881	0,015	0,009			
	V	t-4	5	50	0,957	0,009	0,008	86%	0,013	0,922
		t-4	10	50	0,940	0,003	0,002	84%	0,013	1,018
		t-4	20	50	0,953	0,004	0,003	85%	0,005	0,933
Model -3	C	t-4	5	90	0,944	0,013	0,026			
		t-4	10	90	0,944	0,014	0,014			
		t-4	20	90	0,927	0,015	0,009			
		t-4	100	90	0,844	0,021	0,012			
	V	t-4	5	90	0,990	0,003	0,001	89%	0,027	1,003
		t-4	10	90	0,962	0,005	0,001	87%	0,013	0,948
		t-4	20	90	0,940	0,042	0,004	83%	0,005	0,962
		t-4	100	90	0,955	0,027	0,003	72%	0,010	0,940
Model -4	C	t-6	5	90	0,914	0,013	0,026			
		t-6	10	90	0,895	0,014	0,014			
		t-6	20	90	0,889	0,015	0,009			
	V	t-6	5	90	0,932	0,003	0,001	89%	0,027	1,003
		t-6	10	90	0,967	0,005	0,001	88%	0,013	0,948
		t-6	20	90	0,932	0,042	0,004	86%	0,005	0,962

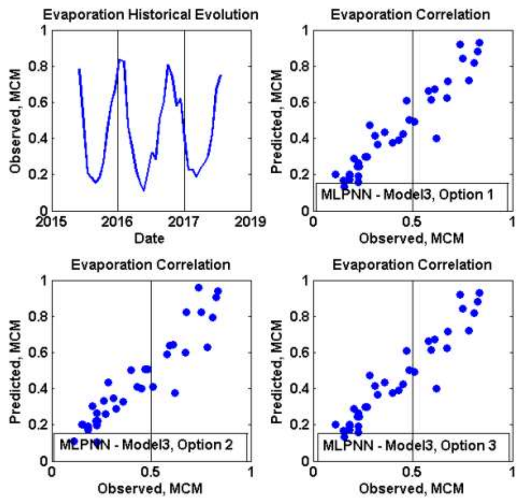

Fig.3 : Correlation of the observed and predicted evaporation

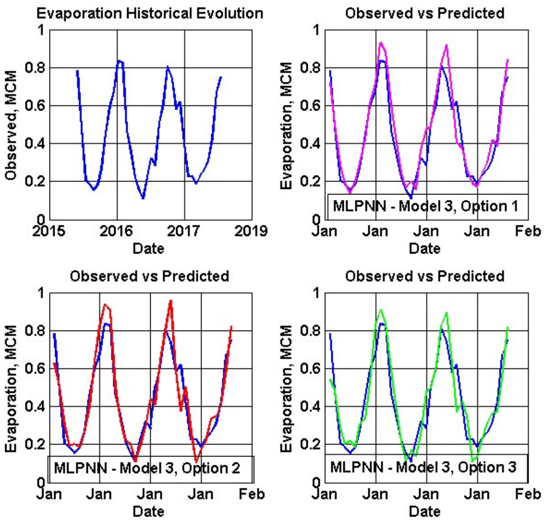

Fig.4: Confrontation of the observed and predicted evaporation

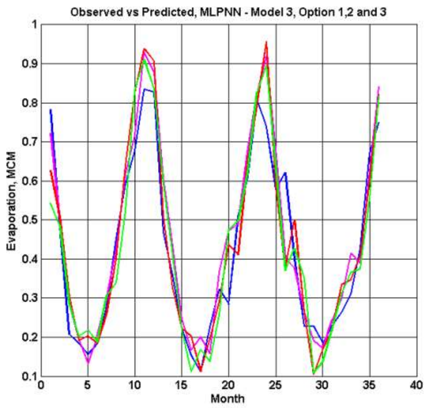

Fig.5: Observed vs predicted evaporation

As to ANFIS model, the best-adopted model involves a rules number (RN), a learning rate (LR) and a lag time of 2, 90%, and t-4, respectively. For assessing the predicted values of evaporation relative to observed ones, obtained performance metrics of CC, RMSE, MSE, NC, {B} and I corresponding to 0,972; 0,004 ; 0,006 ; 93% ; 0,009 and 0,850, respectively. The achieved performance metrics are greatly promising, particularly a Nash coefficient (NC) of 93% higher than 89% resulted from MLPNN model (Table.II). Moreover, by comparing the achieved results, it is clear that both MLPNN and ANFIS models give better outputs. However, ANFIS model is more performing and accurate, as it is shown in the Fig.6, 7 and 8, where the predicted values of evaporation obtained using ANFIS model with two fuzzy rules are more performing than the predicted ones resulted from MLPNN model.

Table II

Performance metrics of the evaporation prediction using **ANFIS** model (**C**: Calibration, **V**: Validation)

		Lag time	NN/ RN	LR %	CC	RMS E	MSE	NC	{B}	I
Model-1	C	2	2	50	0,826	0,016	0,016			
		2	2	90	0,843	0,019	0,031			
		4	2	90	0,816	0,021	0,003			
	V	2	2	50	0,947	0,010	0,011	89 %	0,027	0,975
		2	2	90	0,947	0,004	0,002	88 %	0,033	0,964
		4	2	90	0,972	0,004	0,006	93 %	0,009	0,850

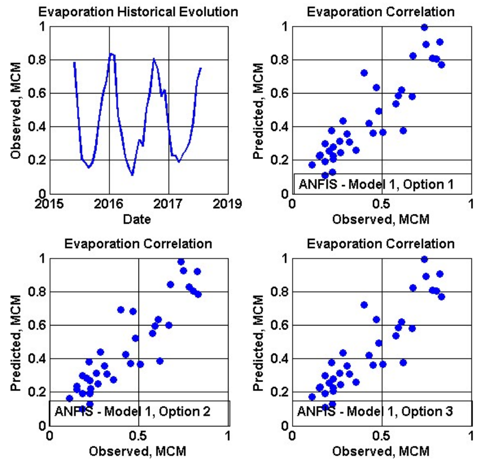

Fig.6: Correlation of the observed and predicted evaporation.

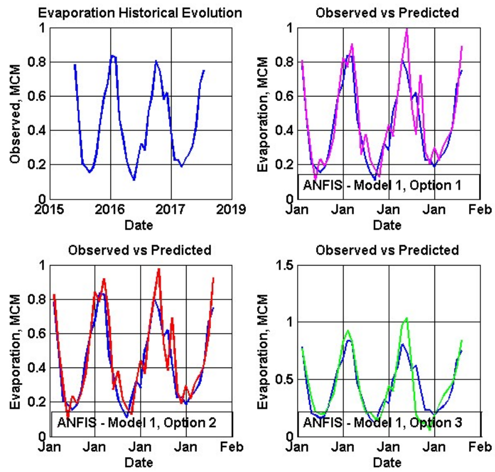

Fig.7: Confrontation of the observed and predicted evaporation.

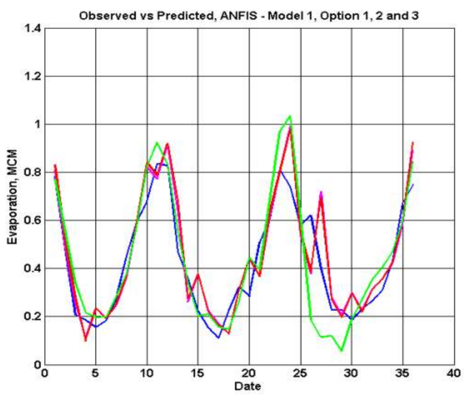

Fig.8: Observed vs predicted evaporation.

2. Inflows prediction

Given the random character of inflows to reservoir, the developed model consists as far as possible, in exploring the performance of ANN methods in predicting random variables. In this case, the adopted multilayer neuronal model « MLPNN », whose NN and LR are 20 and 90%, respectively, has given fair results (Table. III), as it is shown clearly in Fig.9, 10 and 11, a slight difference between the observed and the predicted values with a RMSE lesser than unity in a calibration phase and lesser than two in a validation phase. Nevertheless, a weak correlation is observed. Likewise, ANFIS model gave acceptable predicted values and that, according to performance metrics (Table. IV) and as it is shown in Fig.12, 13 and 14.

Table III
Performance metrics of the inflows prediction using **MLPNN** model
(**C**: Calibration, **V**: Validation)

	Lag time	NN	LR	CC	RMSE	MSE	NC	{B}	I
C	t-2	20	90	-0,745	0,231	0,373			
	t-4	20	90	-0,920	0,413	0,730			
	t-6	20	90	-0,316	0,405	0,735			
V	t-2	20	90	0,212	1,673	2,969	-50 %	3,342	1,767
	t-4	20	90	0,145	1,733	2,737	-65 %	3,467	1,792
	t-6	20	90	0,273	1,703	3,858	-34 %	4,593	1,965

Table IV
Performance metrics of inflows prediction using ANFIS model
(**C**: Calibration, **V**: Validation)

	Lag time	NN	LR	CC	RMSE	MSE	NC	{B}	I
C	2	2	50	0,244	0,923	0,177			
	2	2	90	-0,394	0,237	0,329			
	4	2	90	-0,326	0,357	0,527			
V	2	2	50	0,257	1,244	1,016	-53%	1,193	1,321
	2	2	90	0,240	1,609	1,969	-49%	2,298	1,519
	4	2	90	0,130	1,878	2,197	-48%	2,723	1,367

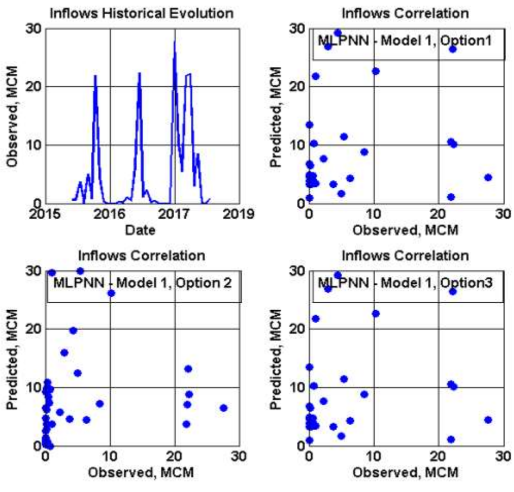

Fig.9: Correlation of the observed and predicted inflows.

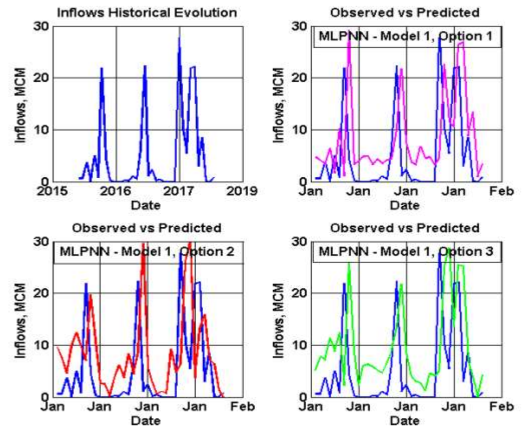

Fig.10: Confrontation of the observed and predicted inflows.

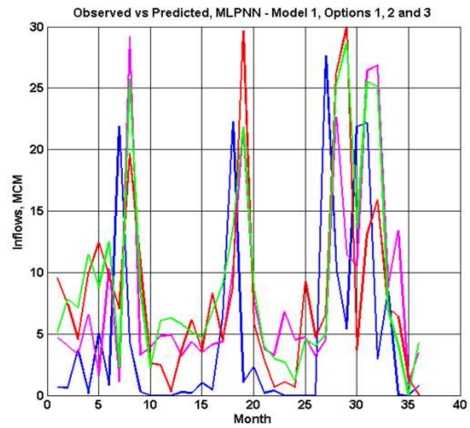

Fig.11: Observed vs predicted Inflows.

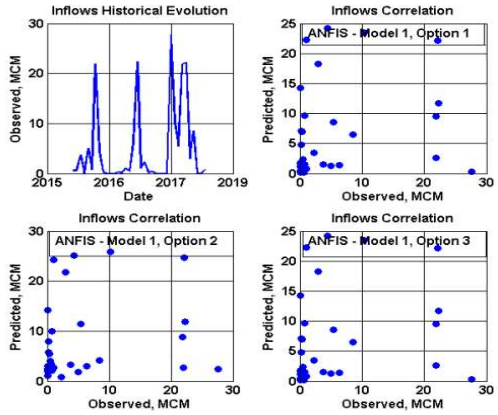

Fig.12: Correlation of the observed and predicted inflows.

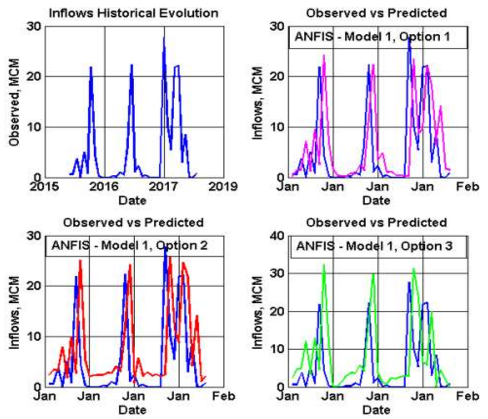

Fig.13: Confrontation of the observed and predicted inflows.

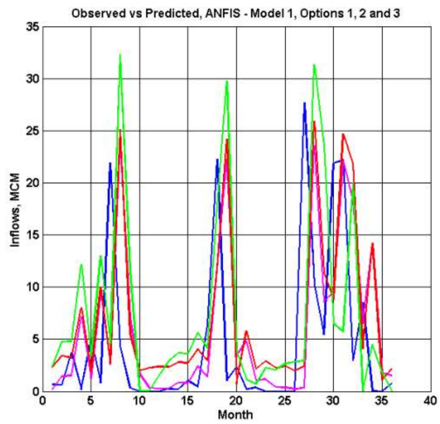

Fig.14: Observed vs predicted inflows.

3. Reservoir storage Prediction

Given the fair results obtained from inflows prediction, on the contrary, the prediction of a reservoir storage attempted with aim of verifying the performance of MLPNN and ANFIS models, is conclusive. Concerning MLPNN model, the second model with 5, 10 and 20 hidden neurons and learning rate of 90% is promising in predicting the reservoir storage according to the achieved performance metrics (Table.V). Thus, the observed and the predicted reservoir storage values are highly correlated with a CC and NC about 0,963 and 93%, respectively. Fig.15, 16 and 17 confirm the robustness and the performance of MLPNN model in predicting reservoir storage.

Table V
Performance metrics of the storage prediction using the model **MLPNN** (**C**: Calibration, **V**: Validation)

		Lag time	NN	LR %	CC	RMSE	MSE	NC	{B}	I
Model -1	**C**	t-2	5	50	0,884	1,907	3,503			
		t-2	10	50	0,861	2,045	3,878			
		t-2	20	50	0,793	2,328	3,598			
	V	t-2	5	50	0,945	0,898	1,107	89 %	4,609	1,024
		t-2	10	50	0,962	0,726	0,582	93 %	4,460	1,027
		t-2	20	50	0,951	0,834	0,769	91 %	4,367	1,042
Model -2	**C**	t-4	5	90	0,870	2,046	0,184			
		t-4	10	90	0,895	1,773	0,078			
		t-4	20	90	0,871	1,944	0,088			
	V	t-4	5	90	0,972	0,306	3,904	94 %	4,088	0,989
		t-4	10	90	0,963	0,178	3,293	93 %	3,372	1,029
		t-4	20	90	0,961	0,253	4,156	92 %	4,244	0,999
Model -3	**C**	t-6	5	90	0,891	1,744	2,044			
		t-6	10	90	0,897	1,672	2,550			
		t-6	20	90	0,862	2,002	3,480			
	V	t-6	5	90	0,953	0,138	0,076	92 %	1,968	0,980
		t-6	10	90	0,950	0,311	0,286	91 %	2,835	1,030
		t-6	20	90	0,936	0,598	0,598	88 %	4,078	0,990

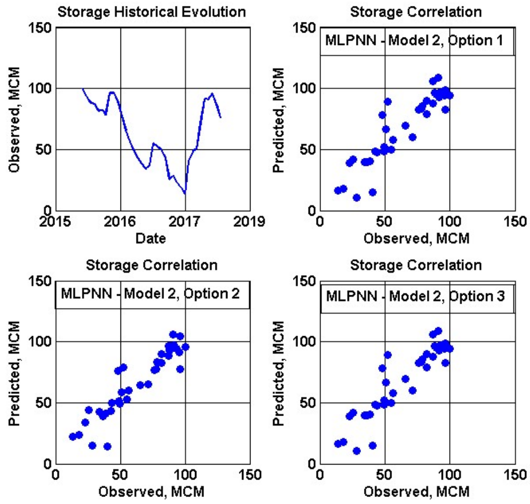

Fig.15: Correlation of the observed and predicted storage.

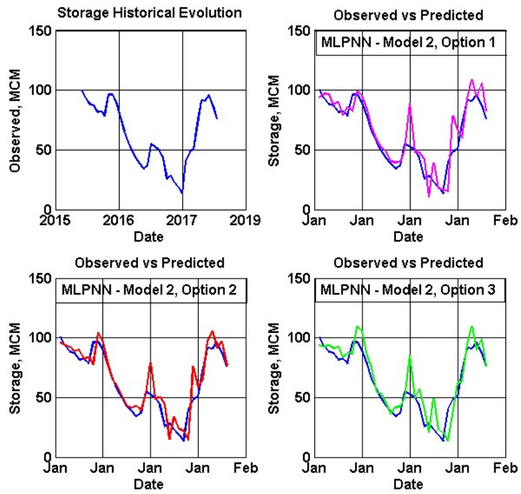

Fig.16: Confrontation of the observed and predicted storage.

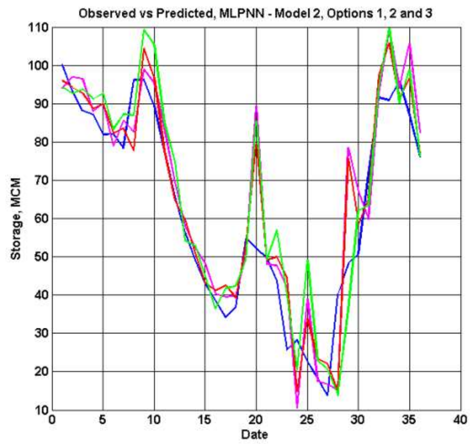

Fig.17: Observed vs predicted storage.

As to ANFIS model, the second option of the first model with two fuzzy rules, a learning rate of 90% and a lag time of t-2 has reached performing metrics by comparing predicted and observed storage values (Table.VI).

The robustness and the accuracy of achieved predicted storage values is confirmed through their confrontation with the observed values as it's shown in Fig.18, 19 and 20.

Table.VI
Performance metrics of the storage prediction using the model **ANFIS** (**C**: Calibration, **V**: Validation)

		Lag time	NN/ RN	LR %	CC	RMSE	MSE	NC	{B}	I
Model-1	C	2	2	50	0,865	1,862	2,457			
	V	2	2	50	0,953	0,797	0,118	79 %	2,575	1,009
	C	2	2	90	0,873	2,032	3,701			
	V	2	2	90	0,956	0,091	0,153	81 %	3,548	0,984
	C	4	2	50	0,746	2,718	2,887			
	V	4	2	50	0,962	0,190	0,146	70 %	3,033	0,915

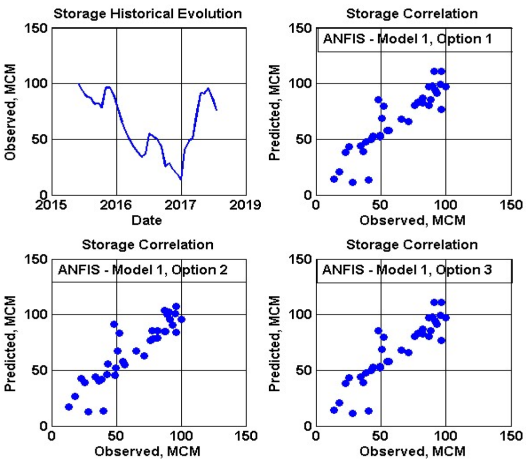

Fig.18: Correlation of the observed and predicted storage.

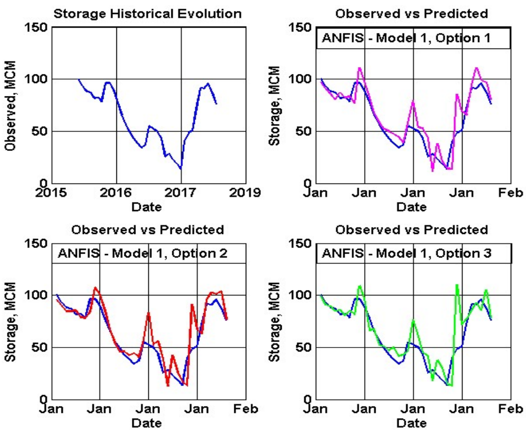

Fig.19: Confrontation of the observed and predicted storage.

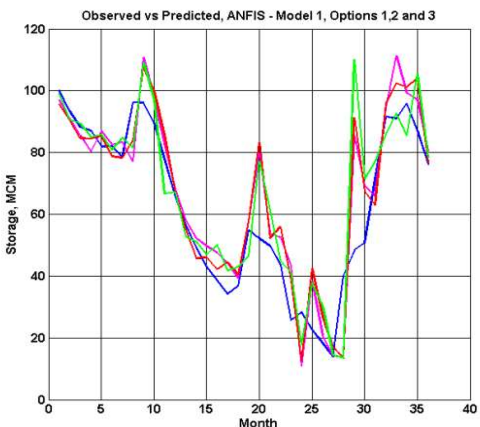

Fig.20: Observed vs predicted reservoir storage.

IV. CONCLUSION

Our approach through this case study consists of predicting state variables such as evaporation, inflows and reservoir storage, with aim of reducing a systematical uncertainty. This is necessary for optimizing the current reservoir operating policy, within the scope of a sustainable and secure water resources management, and therefore, the achieved models based artificial neural networks and fuzzy logic constitute, a decision making tool for a reservoir operator in order to manage releases efficiently. In this respect, given the performance of ANN methods in extrapolating linear or nonlinear data, the developed MLPNN feed forward model based on the supervised learning is tested in predicting reservoir state variables. Generally, the performance of the MLPNN and ANFIS models is demonstrated through the promising reached results related to evaporation and reservoir storage prediction, given the performance metrics of correlation and Nash coefficients widely persuasive. As to inflows, their prediction gave fair outputs, which confirms the inability of conventional MLPNN and ANFIS methods in predicting the random variables. Moreover, I have to note that the developed models enabled in predicting inflows with a root mean square error lesser than unity. Nevertheless, the correlation between observed and predicted values is lesser than unity; this reached result is singular compared with the achieved results related to the random variable prediction based artificial neural networks and fuzzy logic, available in the international literature on web. However, applying artificial neural networks and fuzzy logic helped in improving slightly reservoir-operating policy, in spite of predicting random variables remains a difficult task with these methods, whose classic solutions are not always completely satisfactory and are costly in computation time. In perspective, the future challenge in a matter of random variable prediction with artificial neural networks and fuzzy logic methods is to explore deeply their learning capacity, with aim of developing decision-making tools in a matter of reservoir operation and that, relative to the climate change, region aridity arid conditions of uneven rainfall distribution in space and in time.

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