MODELLING AND PREDICTION OF RAINFALL BY THE NEURO-FUZZY METHOD IN THE SPECIAL RESERVE MAROTANDRANO MADAGASCAR

Télesphore RANDRIAMAITSO[1*], S. Njara RHEVIHAJA[2], F. Philibert ANDRINIRINIAIMALAZA[1], and Théodore TOTOZAFINY[3] and R. Todihasina. RANDRIANANTENAINA[3]

[1]*University of Mahajanga, Higher Institute of Sciences and Technologies, Ex-LOLO Building Mahajanga-be, Madagascar*
[2]*University of Mahajanga, EDGVM Doctoral School, Madagascar*
[3]*University of Mahajanga, Faculty of Sciences, Technologies and Environment, Madagascar*

ABSTRACT

The study area is the Marotandrano Special Reserve, bounded by latitude between 16°S and 16.5°S and longitude between 48°E and 48.5°E.
We modelled rainfall from 1979 to 2018 using the Neuro-flou method. According to this method, the average annual rainfall is between 38.38 mm and 94.8 mm. The year 2005 is the year less watered, the average annual rainfall value is 38.38 mm. The years most watered are the years 2000 and 2040 with an average value of 94.88 mm.

Keyword: - *Rain, forecast, Neuro-fuzzy, Special Reserve Marotandrano.*

1. INTRODUCTION

The intensification of extreme climates is an emerging aspect of climate change that implies an urgent need to improve our understanding of the ecological, agronomic and water reserve consequences for the hydroelectric dam. In the longer or shorter term, what can these brutal and unpredictable phenomena cause [1]? For this, the prevention of climate factors at the ecosystem scale is a necessary approach, because it allows to preserve the biotic and abiotic processes involved in the functioning of the system [2] [3].
In Madagascar, the impact of climate change on rainfall remains a major concern for the Big Island. It is likely to hit the whole country hard in the coming years, especially the Marotandrano special reserve.
And it is for this reason that this study leads us to model the annual average value of rainfall by the Neuro-Fuzzy method. In this perspective, the proposal of a model of medium-term forecasting in a study area is essential to conduct this study.

2. MATERIAL AND METHODS

2.1 Presentation of the study area

The study area (see Figure 1) is located between latitude 16°South and 16,5°South and longitude 48° East and 48,5° East.

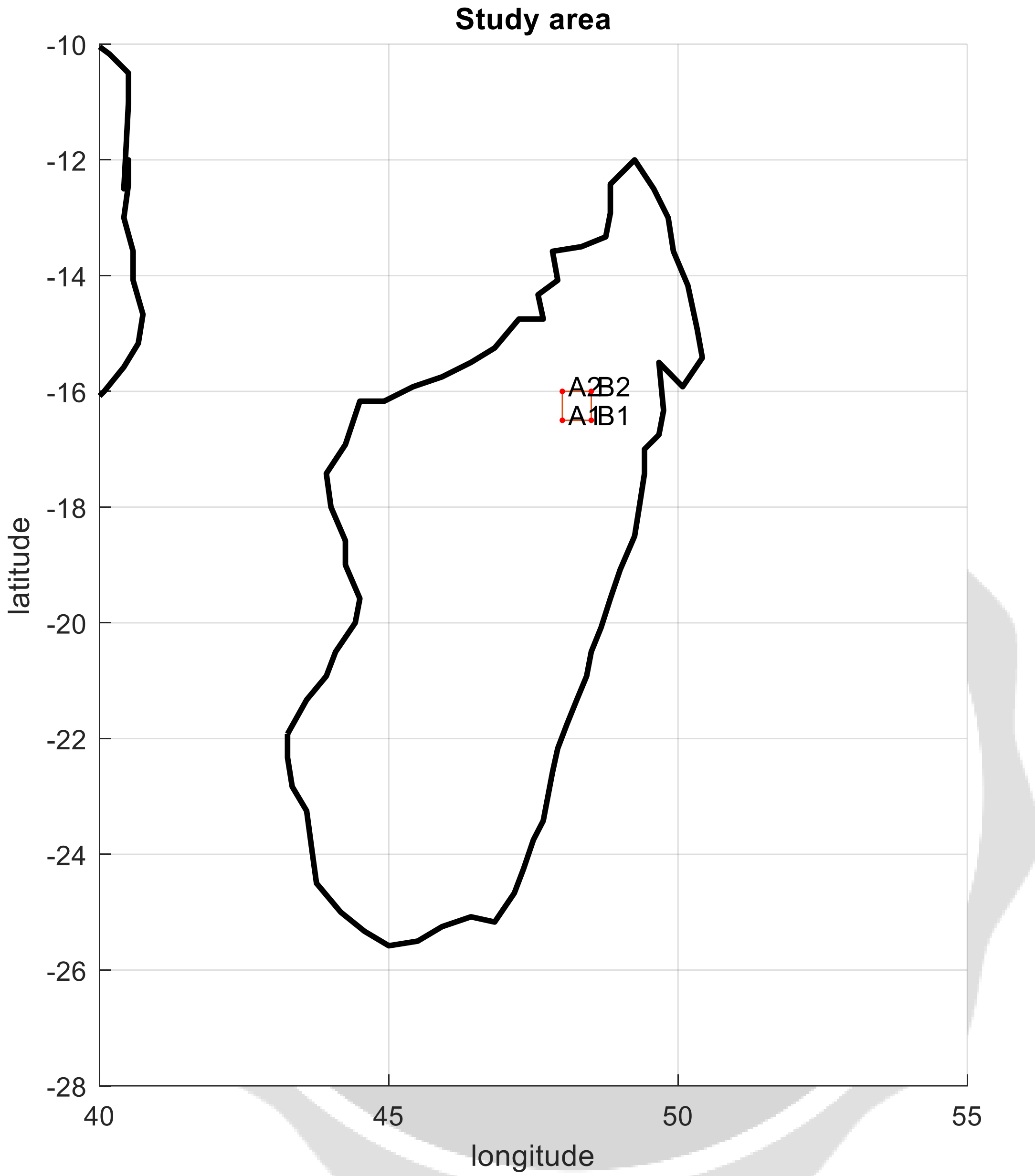

Fig -1: Study area 48°≤ longitude ≤ 48.5° and -16°≤ latitude ≤ -16.5°

2.2 Databases

The meteorological data we used are from the European Centre for Medium range Weather Forecasts (ECMWF) daily reanalysis experiment (ERA5) data at synoptic scale with a 0.5° x 0.5° grid of rainfall over a time depth covering the period 1979-2018.

2.3 Neuro-fuzzy modelling

2.3.1 Definition

Neuro-fuzzy systems combine the advantages of two complementary techniques. Fuzzy systems provide a good knowledge representation.

The integration of neural networks within these systems improves their performance thanks to the learning capacity of neural networks. Conversely, the injection of fuzzy rules into neural networks, which are often criticized for their

lack of readability, clarifies the meaning of the network parameters and facilitates their initialization, which represents a considerable saving in computation time for their identification.
The Neuro-Fuzzy system refers to the way of applying various learning techniques developed in the neural network literature to the fuzzy inference system.
In order to clarify the definitions, we propose in this chapter a brief presentation of some types of Neuro-fuzzy systems and a more detailed presentation of ANFIS.

2.3.2 Some types of neuro-fuzzy combination

There are several types for combining neural networks and fuzzy systems. These types can be classified into functional and structural, depending on their architecture and the research configuration between the fuzzy inference system and the neural networks.

2.3.3 Cooperative and concurrent neuro-fuzzy systems [4] [5] [6]

A cooperative neuro-fuzzy system can be considered as a preprocessor where the learning mechanism of artificial neural networks (ANNs) determines the fuzzy inference system (FIS) membership functions or fuzzy rules from the training data. Once the FIS parameters are determined, ANN goes to the bottom. The based rule is usually determined by a fuzzy clustering algorithm. The membership functions are usually approximated from ANN by the training data.
In a concurrent neuro-fuzzy system, ANN helps the RIS continuously to determine the required parameters especially if the input variables of the controller cannot be measured directly. In some cases the outputs of RIS may not be directly applicable to the process. Figures 2 and 3 represent the cooperative and concurrent Neuro-Fuzzy models.

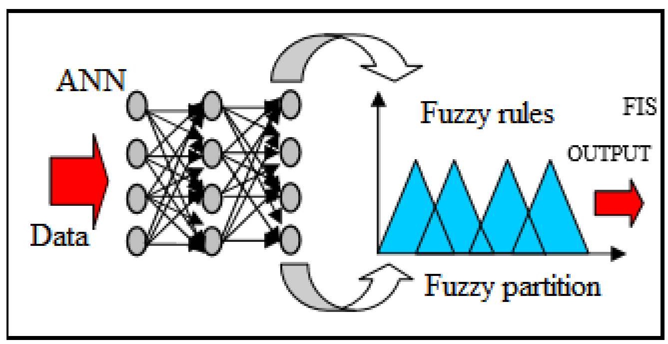

Fig -2: Cooperative neuro-fuzzy system

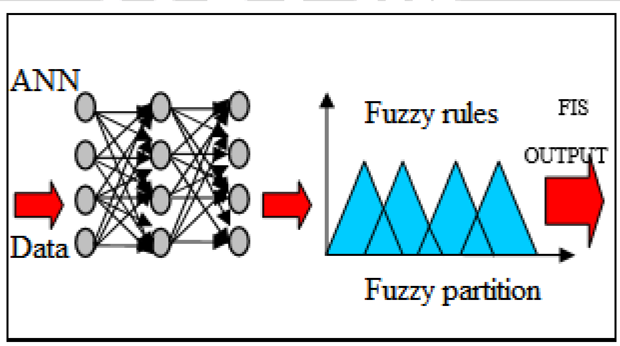

Fig -3: Competing Neuro-fuzzy system

2.3.4 Fused neuro-fuzzy systems

In a fused neuro-fuzzy architecture, ANNs are used to determine the parameters of RIS. Fused Neuro-fuzzy systems share data structures and knowledge representation. A usual way to apply a learning algorithm to a fuzzy system is to represent it in a special architecture.

2.3.5 Falcon (Fuzzy Adaptive Learning Control Network) [7]

Falcon has a five-layer architecture, as shown in Figure 4.

There are two neurons for each output variable. One for the training data (desired output) and the other is for the output of FALCON. The first hidden layer is used to fuzzify the input variables. Each neuron in this layer represents a fuzzy set membership function. The second hidden layer defines the antecedent parts of the fuzzy rules followed by the consequence parts of the rules in the third hidden layer. FALCON uses a hybrid learning algorithm involving unsupervised learning to locate membership functions and initial rule bases and supervised learning to optimize the adjustment of the FM parameters to generate the desired outputs.

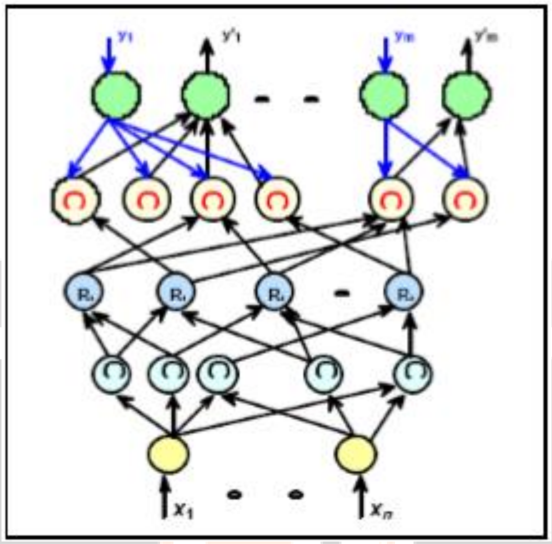

Fig -4: Architecture of FALCON

2.3.6 NEFCON (NEuro-Fuzzy CONtrol) [8]

NEFCON is designed to implement the Mamdani type fuzzy inference system. It consists of two layers whose weights are the fuzzy sets and the fuzzy rules. With the same assumed prior use shared weights, which are represented by ellipses drawn around the connections. They ensure the integrity of the rule base. The input layer provides the task of the fuzzification interface, the inference logic is represented by the propagation functions, and the output layer is the defuzzification interface. The learning of the NEFCON model is based on a mixture of unsupervised and supervised learning (back-propagation). NEFCON can be used to learn initial rules, if no system knowledge is available or even to optimize a manually defined rule base.

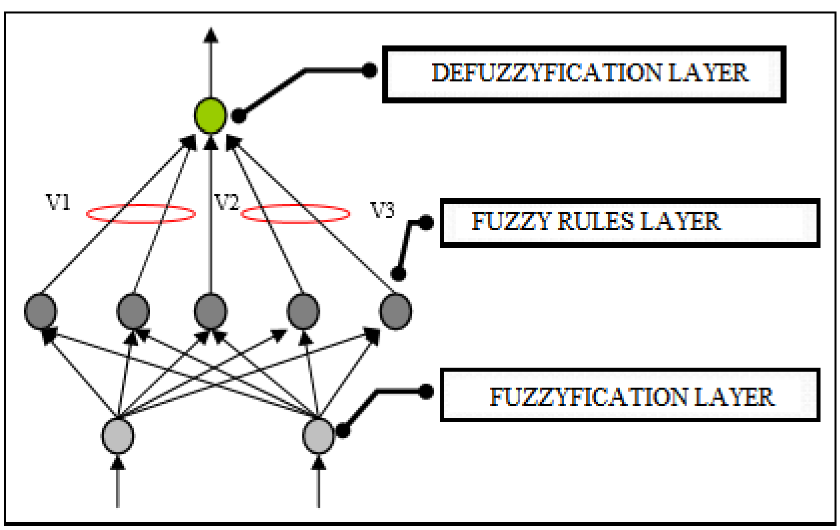

Fig -5: Architecture of NEFCON

2.3.7 ANFIS model [9] [10] [11]

ANFIS (Adaptive Network Based Fuzzy Inference System) is a neuro-fuzzy adaptive inference system that consists of using a 5-layer MLP neural network for which each layer corresponds to the realization of a step of a Takagi Sugeno type fuzzy inference system. For simplicity, we assume that the fuzzy inference system has two inputs x and y, and one output f. Assume that the rule base contains two Takagi-Sugeno fuzzy rules.

Rule1: $if(x\ is\ A_1)\ and\ (y\ is\ B_1)\ then(f_1 = p_1x + q_1y + r_1)$ (1)

Rule2: $if(\ x\ is\ A_2)\ and\ (y\ is\ B_2)\ then(f_2 = p_2x + q_2y + r_2)$ (2)

ANFIS has a five-layer architecture as shown in Figure 6.

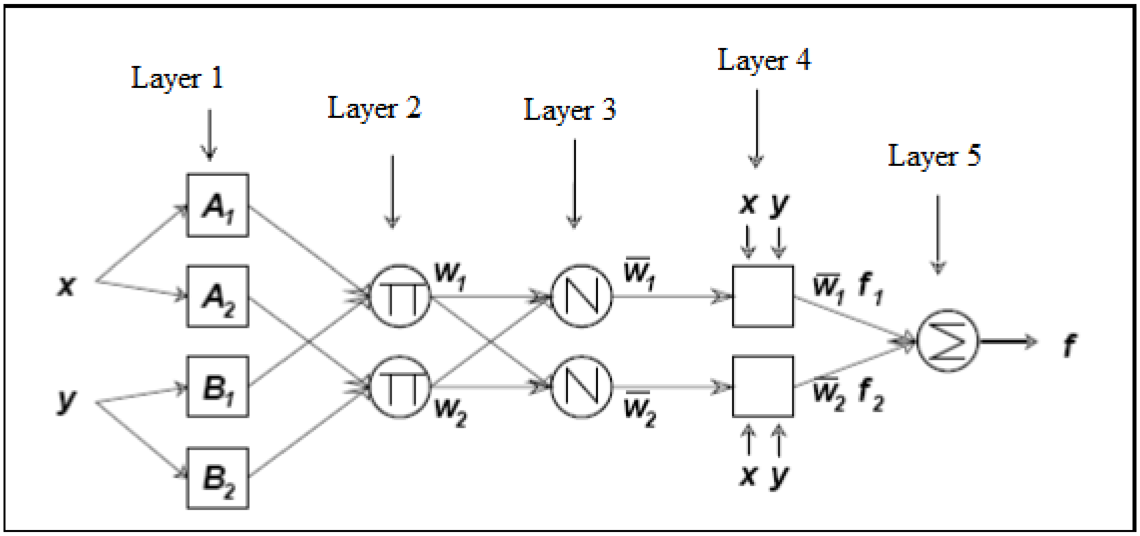

Fig -6: Architecture of ANFIS

A typical architecture can be described as follows:

1. The first layer of an ANFIS architecture has as many neurons as there are fuzzy subsets in the represented inference system. Each neuron calculates the truth degree of a particular fuzzy subset by its transfer function. The only restriction on the choice of this function concerns its derivability. In the literature, Gaussian functions are used and the modifiable parameters are the center and the slope of the Gaussian (variance).

The activation function of the neurons i of the first layer:

$$f_i^1 = \mu_{Ai}(X) \quad (3)$$

Where X is the input to neuron i, and Ai is a fuzzy subset corresponding to variable x. In other words, f_i^1 is the membership function of Ai and it indicates the degree to which given X satisfies the quantifier Ai. We choose $\mu_{Ai}(X)$ to be (Gaussian, triangle, trapezoidal) shaped with maximum equal to 1 and minimum equal to 0, such that the generalized functions of these shapes is:

Triangle: $\mu(x) = \max(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0)$ (4)

Trapezoidal: $\mu(x) = \max(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0)$ (5)

Gaussian: $\mu(x) = \exp\left(-\frac{(x-c)^2}{\sigma^2}\right)$ (6)

Where {a, b, c, σ} is the set of parameters. As the values of these parameters change, the functions in the previous form change accordingly, thus presenting various forms of membership function on the linguistic variable Ai. The parameters in this layer are referred to as membership function parameters.

2. The second hidden layer is used to calculate the degree of activation of the premises. The neurons in this layer each represent the premise of a rule. They receive as input the degree of truth of the different fuzzy subsets composing this premise and are in charge of computing its own degree of truth. The activation functions used for these neurons depend on the operators present in the rules (AND or OR).

The activation function of the neurons i of the first layer:

$$W_k = \mu_{Ai}(X) * \mu_{Bj}(Y) \tag{7}$$

Where k: represents the number of rules, i: represents the number of partitions of X, and j: the number of partitions of Y.

3. The third hidden layer normalizes the degree of rule activation. Each neuron in this layer is a circle neuron denoted N. The i^{th} neuron calculates the ratio between i^{th} rule weight and the sum of all rule weights. This operation is called weight normalization.

$$\overline{W_k} = \frac{w_k}{\sum w_i} \tag{8}$$

The set of outputs from this layer will be called the normalized weights.

4. The fourth hidden layer is used to determine the parameters of the consequence part of the rules (p, q, r). The function of each neuron in this layer is as follows

$$f_k^4 = \overline{W_k} * f_k = \overline{W_k}(p_k x + p_k y + r_k \tag{9}$$

Where W_k is the output of the third layer, and $\{r_i, q_i, p_i\}$ is the set of parameters. These parameters are referred to as the consequential parameters.

5. The output layer contains a single neuron in this layer, is a circle neuron denoted S which calculates the overall output as the sum of all incoming signals, that's to say:

$$f^5 = \sum_k \overline{W_k} * f_k^4 \tag{10}$$

Figure 7 shows an ANFIS system, with 2 inputs each divided into three fuzzy subsets and 9 rules.

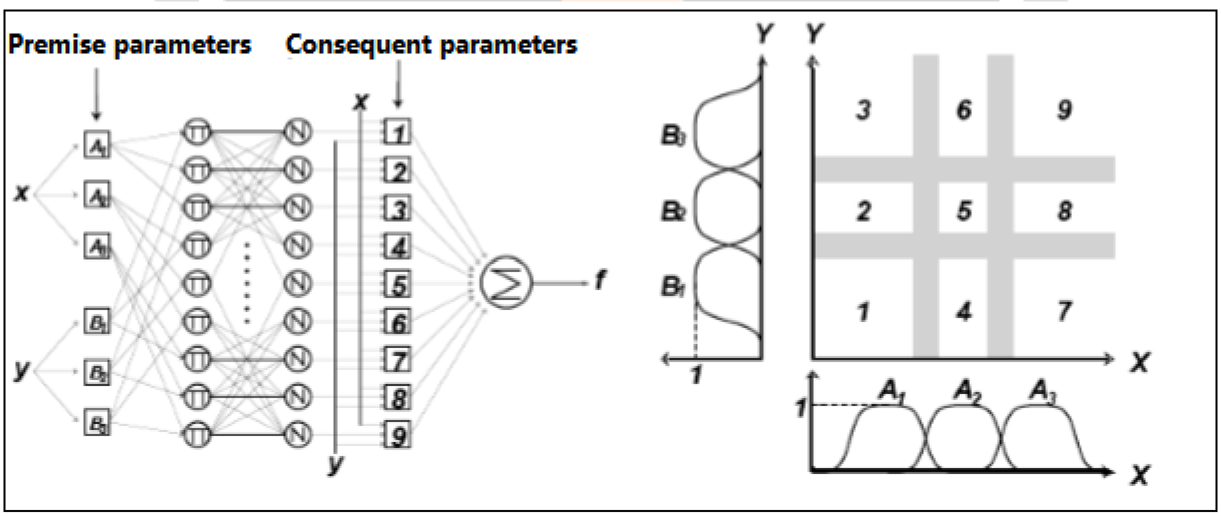

Fig -7: Example ANFIS with 2 inputs and 9 rules

Table -1: Different layers of an ANFIS system

Different layers	Type of the layers	Number of neurons in the layer
Layer 0	Inputs	n
Layer 1	Values	(p. n)
Layer 2	Rules	p^n

Layer 3	Normalization	p^n
Layer 4	Linearization of the functions	p^n
Layer 5	Sum	1

Such that:
n: the number of inputs.
p: the number of fuzzy input subsets (fuzzy partition).

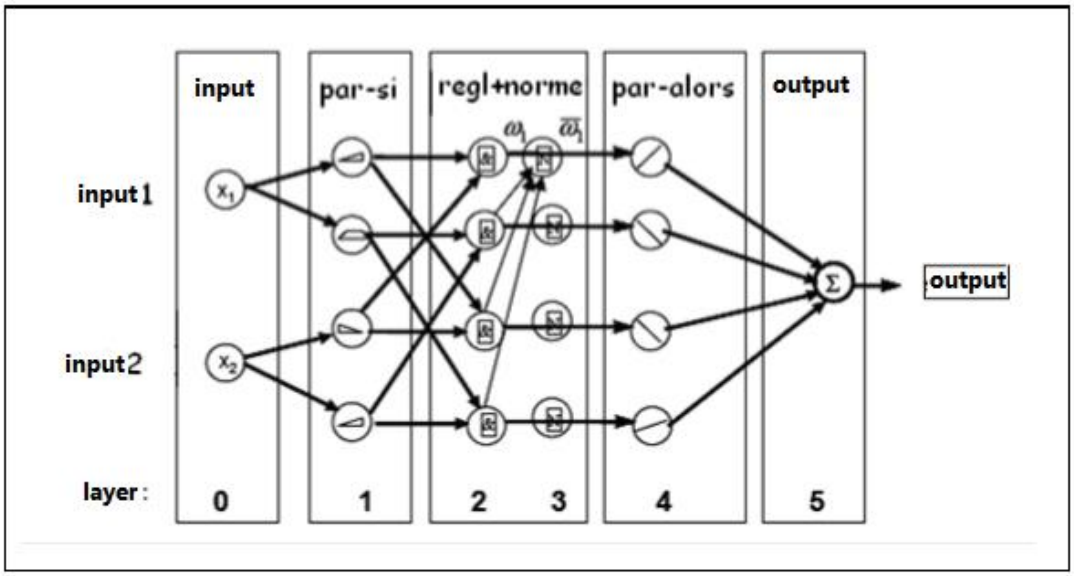

Fig -8: ANFIS network

Note that neurons in ANFIS have different structures:

- Values [membership function defined by different forms];
- Rules [usually product];
- Normalization [sum and arithmetic division];
- Functions[linear regressions and multiplication with $\overline{w}$, such that $\overline{w}$ is the normalization of the weight w];
- Output [Algebraic Sum].

2.3.8 ANFIS learning algorithm

ANFIS applies the learning mechanism of neural networks to fuzzy inference techniques. In other words, ANFIS is a fuzzy inference system (FIS) whose membership function parameters are adjusted using the back-propagation learning algorithm, or in combination with another type of algorithm such as least square.

In the ANFIS architecture proposed in Figure 6, the overall output can be expressed as linear combinations of the resulting parameters. More precisely, the conclusion (the output) in Figure 6 can be rewritten as:

$$f = \frac{W_1}{W_1+W_2} f_1 + \frac{W_2}{W_1+W_2} f_2$$
$$= (\overline{W_1}x)p_1 + (\overline{W_1}y)q_1 + (\overline{W_1})r_1 + (\overline{W_2}x)p_2 + (\overline{W_2}y)q_2 + (\overline{W_2})r_2 \quad (11)$$

The output is a linear function of the consequence parameters (p, q, r). ANFIS is a parametric representation of two sets of parameters: S1 and S2 such that:

- S1 represents the parameters of the fuzzy sets used for fuzzification in the first ANFIS layer

$$S1 = \left\{\{a_{11}, b_{11}, c_{11}\}, \{a_{12}, b_{12}, c_{12}\}, \dots, \{a_{1p}, b_{1p}, c_{1p}\}, \dots, \{a_{np}, b_{np}, c_{np}\}\right\} \quad (12)$$

Where p is the number of fuzzy partitions of each of the input variables and n is the number of input variables.

- S2 represents the coefficients of the linear functions (the consequent parameters)

$$S2 = \{p_1, p_2, p_3 \dots, q_1, q_2, q_3 \dots, r_1, r_2, r_3 \dots\} \quad (13)$$

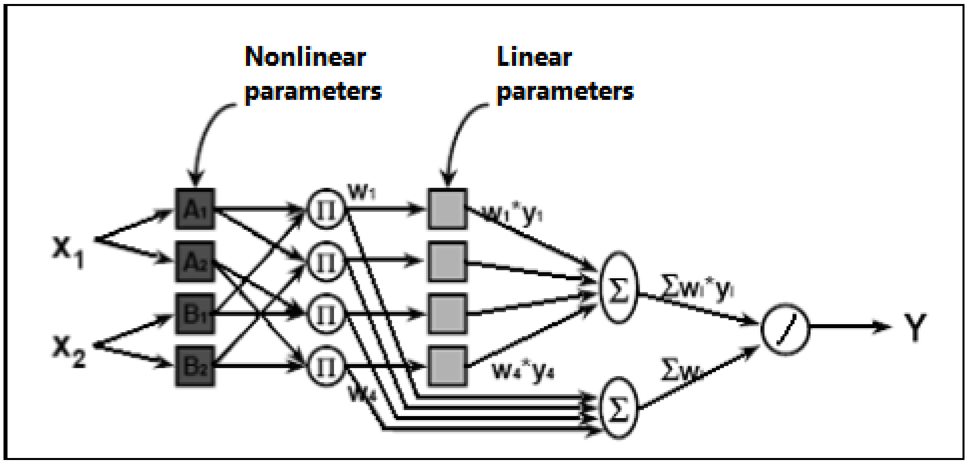

Fig -9: Hybrid learning method

Table -2: Parameters to be adjusted of an ANFIS system

	Passage Forward	Passage Backward
Membership function parameter (nonlinear a_i, b_i, c_i)	fixed	Retro propagation
Coefficient parameter (Linear p, q, r)	least squares	fixed

ANFIS uses a two-pass learning cycle:

- The forward run: S1 is fixed and S2 is calculated using the least square error (LSE) algorithm; (The LSE is applied only once when starting to obtain the initial values of the resulting parameters)
- Backtracking: S2 is fixed and S1 is calculated using the Back propagation algorithm.

2.4 Model validation

Validation makes it possible to judge the ability of the model to reproduce the modeled variables. Several criteria ex bist. In our case, we based ourselves on the correlation coefficient (R).

$$R = \frac{\frac{1}{N}\sum_{i=1}^{N}(Y_{iobs} - \bar{Y}_{obs})(Y_{ical} - \bar{Y}_{cal})}{\sigma_{obs}\sigma_{cal}} \quad (14)$$

With: Y_{iobs} and Y_{ical} correspond respectively to the values observed and calculated by the model for period i, $\bar{Y}_{obs}$ and $\bar{Y}_{cal}$ are the averages of the values observed and calculated by the model, σ_{obs} and σ_{cal} the standard deviations of the values observed and calculated and N: number of periods used.

A perfect positive correlation if the correlation coefficient is close to +1; a perfect negative correlation if the correlation coefficient is close to -1, while an absence of correlation corresponds to a coefficient equal to zero.

3 RESULTS AND DISCUSSION

3.1 Graphical representation of the model

Figure 10 show the forecasts of the average annual rainfall observed during the study period. The curves of the observed data in blue and the curves in purple are the forecast models. The forecast values of the annual average rainfall for the years 2019 to 2042 are shown in Table 3.

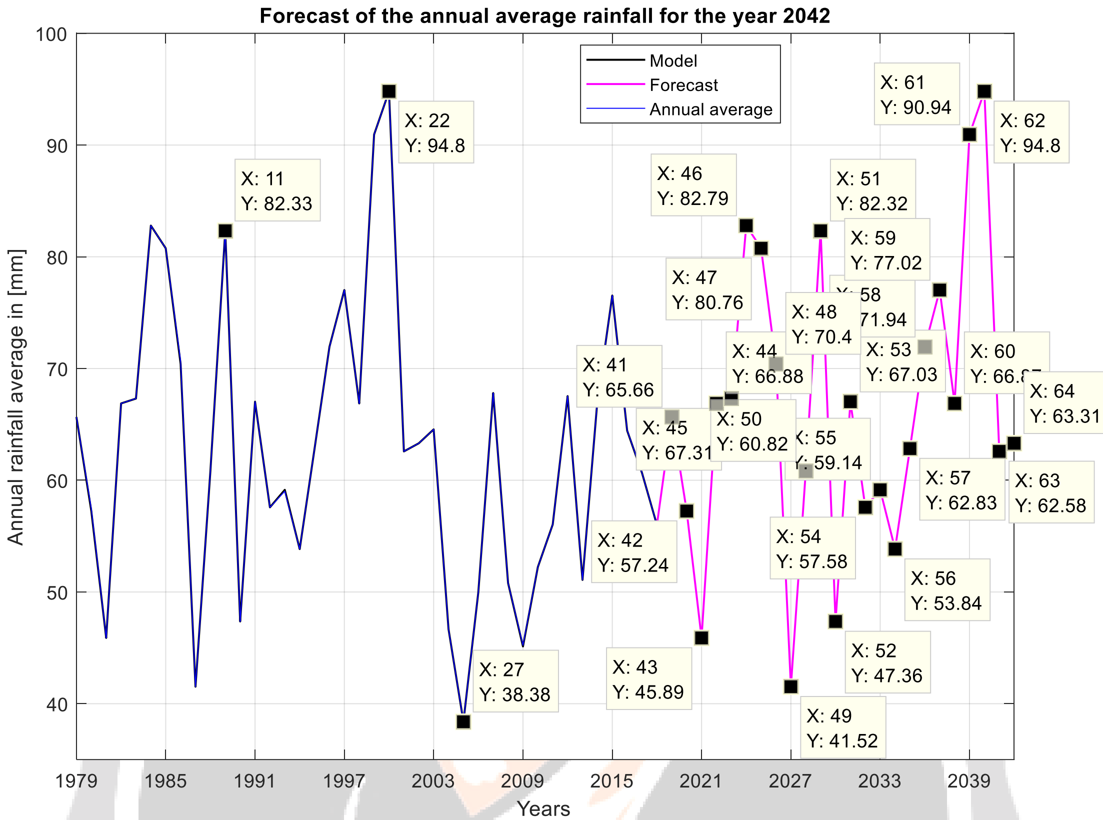

Fig -10: Rainfall prediction curve for 2042

Table -3: Forecast of the annual average rainfall by the Neuro-fuzzy method

Years of the forecast	Values of the annual average rainfall in [mm].
2019	65.66
2020	57.24
2021	45.89
2022	66.88
2023	67.31
2024	82.79
2025	80.76
2026	70.40
2027	41.52
2028	60.82
2029	82.32
2030	47.36
2031	67.03
2032	57.58
2033	59.14
2034	53.84
2035	62.83
2036	71.94
2037	77.02
2038	66.84
2039	90.94
2040	94.80
2041	62.58

2042	63.31

When analyzing the curves, the average rainfall values range from 38.38 mm to 94.80 mm. The minimum value is 38.38mm (in 2005) and the maximum value is 94.80 mm (in 2000 and in 2040).

3.2 Model validation criteria

Figure 11 shows the correlation curves.

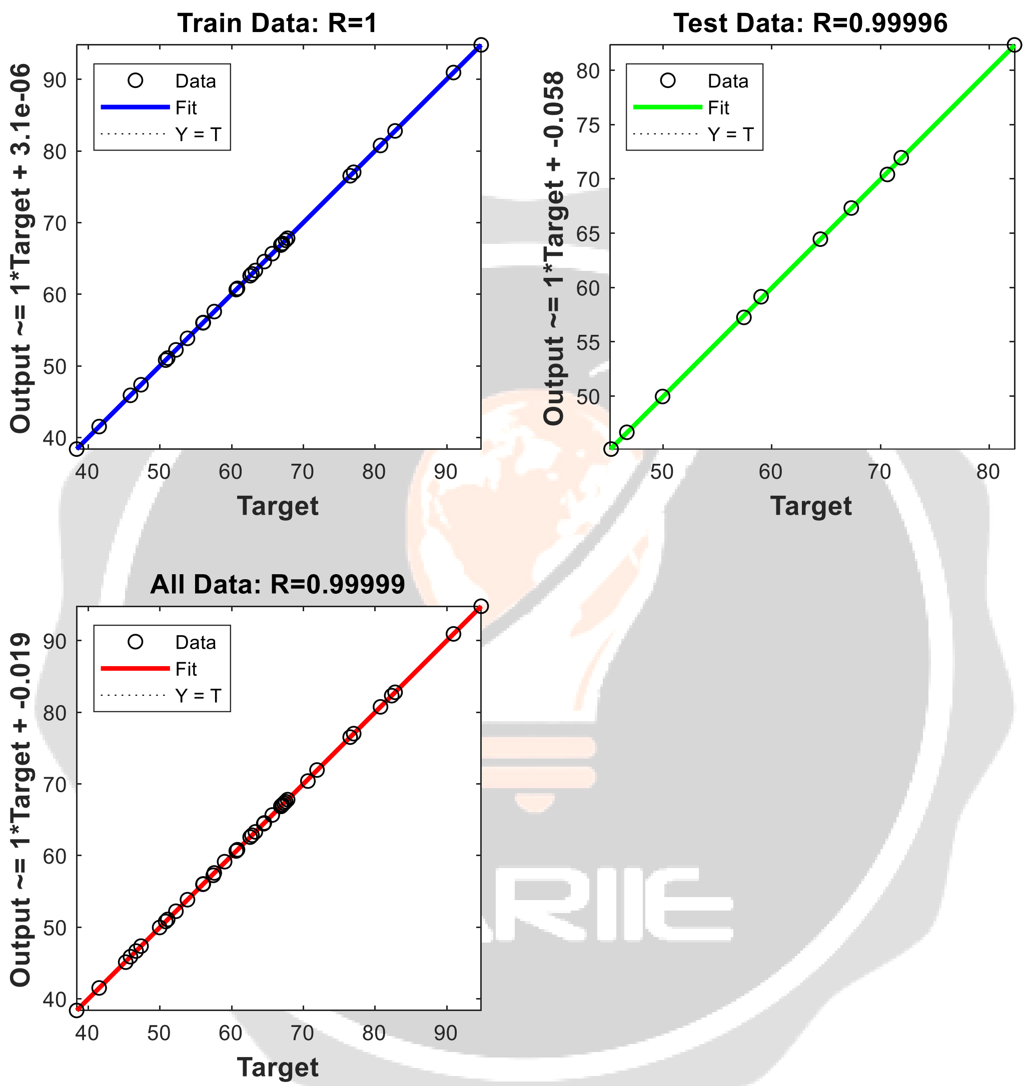

Fig -11: Correlation curve

The correlation coefficient (R) values for this model are: 0.99996 and 0.99999. Both values are close to 1. In fact, the simulation results show that our models for determining rainfall forecasts are excellent.

4. CONCLUSION

In this article, we are interested in the quantitative analysis of daily rainfall from 1979 to 2018 in the Marotandrano Madagascar Special Reserve. This area lies between longitude 48°East and 48.5°East, latitude 18.5°South and 18°South. To study the predictability of these parameters, it is necessary to carry out a quantitative study of some climatological parameters. In our case, we used a statistical method, the Neuro-fuzzy method.

According to the Neuro-fuzzy method, the models selected for average rainfall values range from 38.38 mm to 94.8 mm. 2005 is the least rainy year, with an average rainfall value of 38.38 mm. The wettest years are 2000 and 2040, with an average rainfall value of 94.80 mm.
This method has led us to model the average rainfall values for the years 2019 to 2042 in Table 3.

REFERENCES

[1] IPCC (2012) *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (CB Field, V Barros, TF Stocker, *et al.*, Eds.). Cambridge University Press, Cambridge, United Kingdom.
[2] Jentsch A, Kreyling J, Beierkuhnlein C (2007) A new generation of climate-change experiments_: events , not trends. *Frontiers in Ecology and the Environment*, 5, 365–374.
[3] Beier C, Beierkuhnlein C, Wohlgemuth T, *et al.* (2012) Precipitation manipulation experiments - challenges and recommendations for the future. *Ecology Letters*, 15, 899–911.
[4] B. Kosko, Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence, Prentice Hall, Englewood Cliffs, New Jersey, 1992. 54
[5] H. Nomura, I. Hayashi and N. Wakami, A Learning Method of Fuzzy Inference Systems by Descent Method, In Proceedings of the First IEEE International conference on Fuzzy Systems, San Diego, USA, pp. 203–210, 1992. 54, 56
[6] W. Pedrycz and H.C. Card, Linguistic Interpretation of Self Organizing Maps, In Prroceedings of the IEEE International Conference on Fuzzy Systems, San Diego, pp. 371–378, 1992. 54, 55
[7] C.T. Lin and C.S.G. Lee, Neural Network based Fuzzy Logic Control and Decision System, IEEE Transactions on Comput. (40(12): pp. 1320–1336, 1991. 53, 54, 60, 62, 63
[8] D. Nauck and R. Kruse, NEFCON-I: An X-Window Based Simulator for Neural Fuzzy Controllers. In Proceedings of the IEEE International Conference on Neural Networks, Orlando, pp. 1638–1643, 1994. 60, 64
[9] Jang, J. - S.R., Sun, C. - T., and Mistune, E., 1997, Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, Prentice Hall, New Jersey.
[10] Jang, J.-S.R., 1992, Neuro-Fuzzy Modeling: Architectures, analyses, and Applications, Doctoral Dissertation, California: University of California at Berkeley Publisher.
[11] Jang, Jyh-Shing Roger, 1993, “ANFIS: Adaptive-Network-Based Fuzzy Inference System,” IEEE Transactions on Systems, Man, and Cybernetics, 23(3), 665-685.