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EUTROPHICATION MODELING BY USING MLP-BP BASED ON LEVENBERG-MARQUARDT ALGORITHM: A CASE STUDY

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***Abstract*—This study deals with the Tiagba lagoon bay eutrophication modeling by using Artificial Neural Networks (ANN), principally by using Multilayer Back-propagation based on Levenberg-Marquardt algorithm. 10 or 11 inputs variables, temperature (T), pH, dissolved oxygen (DO), NH_4^+, $NO_3^-$and PO_4^{3-}, monthly precipitation (MP), monthly debit of river Bandama (DBan), suspended matters (SM), transparence (Trans), date of sampling (DS) were used respectively for static and dynamic modeling, while one output variable (chlorophyll a) was considered for the both case. For optimization of the ANN, it was shown that the architecture 10-11-1 was the most suitable for the static modeling of chlorophyll a while the 11-11-1 architecture was the best for dynamic modeling. The validation of these models was performed by analyzing the residues. It was found that theses residues were well distributed between 0.3 and 0.4% and followed a normal law according the Henry representation in the both case. So the models obtained were suitable for the prediction of the chlorophyll a an evolution in relation of the above variables.**

***Key words*— pollution, eutrophication modeling, MLP- BP, L-M algorithm, Tiagba's lagoon bay, Côte d'Ivoire.**

I. INTRODUCTION

Eutrophication is one of common major problems of water bodies. This phenomenon is due to the high presences of nitrogen and phosphorus [1-15]. Nitrogen and phosphorus are both its limiting factors [16-22], whereas phosphorus is only mastery factor [16]. Eutrophication causes the destruction of ecosystem (loss of biodiversity of waters bodies, health risks for man and animals, hindrance of the anthropogenic activities, etc.). In order to gauge how to best prevent eutrophication from occurring, modeling seems to be one of the suitable ways. However, linear models are less suitable than the nonlinear models in eutrophication prediction because of the complex physical, chemical and biological process involved [23-29]. Among the nonlinear models, Artificial Neuron Network (ANN) are becoming more and more common to be used in development of prediction models for complex systems as the theory behind them develops and the processing power of computers increase. There is a lot of ANN. MultiLayer Perceptron based on Back Propagation algorithm (MLP-BP) is one of them. Efficacy of this model in eutrophication prediction and in the description of hydrological phenomenon is well-known.

The great major of Ivoirian water bodies are affected by eutrophication phenomenon. That's the case of Tiagba's lagoon bay. Known for its traditional houses built on the stilts, Tiagba is one of the tourist attractions of Côte d'Ivoire. Therefore, it plays an important role in the socio-economic development of this country. Its lagoon-bay presents a bad state today [33]. So, it's important to take decisions for its rehabilitation and its protection. In this context, this study concerning eutrophication prediction by MLP-BP based on Levenberg-Marquardt (L-M) algorithm in this bay was led. The static and dynamic studies were considered in this case.

II. GENERALITIES ON MLP-BP BASED ON L-M ALGORITHM

A. MLP-BP

In its standard conception, MLP has one input layer, at least one hidden layer and one output layer. However, theoretical works have shown that a single hidden layer is sufficient for an ANN to approximate and any complex nonlinear function [34-35]. That justifies it currently use with one hidden layer

(Fig.1). Each neuron of one layer is connected with the neurons of other layers. There isn't connection between neurons of same layer. A weight is affected at each connection. There isn't defined function on neurons of input layer. On the hidden neurons, sigmoid function (1) is used as active function whereas on output neurons it's used simple linear function (2) as active function. The network isn't back-active and it's synchronic.

$$f(x) = \frac{1}{1+\exp(\alpha x)} \quad (1)$$

$$f(x) = x \quad (2)$$

At each hidden neuron j, the inputs pass through a weighted sum to obtain an output layer vector yi as:

Where x_i is the input, w_{ij} are the weights associated with each input/node connection, and b_j is the bias associated with node j. This sum is used in nonlinear activation function as:

$$y_s = Tanh\left(\sum_{j=1}^{n} w_j y_j\right) + b_s \quad (4)$$

Where y_s is the output of hidden layer, w_j are the weights associated with each input/node connection between the hidden neurons and output neurons, and b_s is the bias associated with node s. So, the output of the hidden layer, y_s, acts as the final output of the network.

Traditional MLP uses Back-Propagation (BP) algorithm with gradient descent technique such as algorithm learning. It's a supervised algorithm. It consists to send back errors committed by one neuron at his nodes and the neurons which are linked. In the same time, errors are corrected following their importance. The weights which contribute to have the important errors are more modified than those committing the minimal errors. However, this algorithm gives the direction where to go to find the minimum but don't give the step. In BP algorithm with gradient descent technique, the step is fixed and in adaptation variable it can take any values at the different iterations. To favour a best learning of MLP-RP, many algorithms, coming from statistical theory, are associated at BP algorithm with gradient descent technique. Among them there's Levenberg-Marquardt algorithm (L-M algorithm) [36-37].

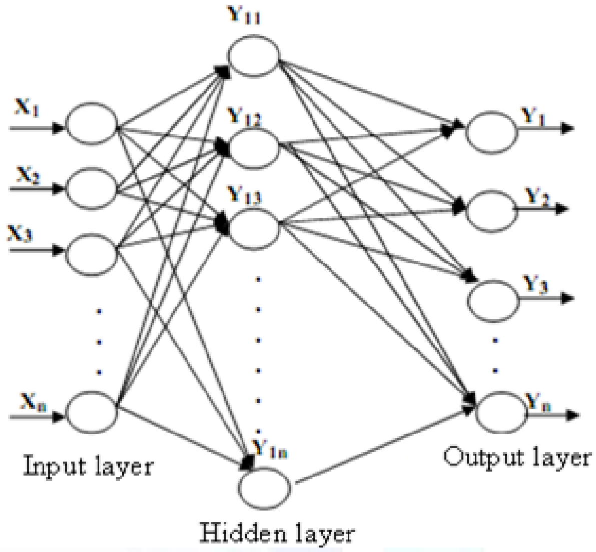


Fig.1. MLP with one hidden layer

B. L-M algorithm

While the BP algorithm with gradient descent technique is a steepest descent algorithm, the L-M algorithm is an approximation to Newton-Gauss method. If a function V(x) is to be minimized with respect to the parameter vector x, then Newton's method would be:

$$\Delta \vec{x} = -[\nabla^2 V(\vec{x})]^{-1} \nabla V(\vec{x}) \quad (5)$$

Where is Hessian matrix and is the gradient. If V(x) reads:

$$V(\vec{x}) = \sum_{i=1}^{N} e^2(x) \quad (6)$$

Then it can be shown that

$$\nabla V(\vec{x}) = J^T(\vec{x})\,\vec{e}(\vec{x}) \quad (7)$$

$$\nabla^2 V(\vec{x}) = J^T(\vec{x})\,J(\vec{x}) + S(\vec{x}) \quad (8)$$

Where is Jacobian matrix and

$$S(\vec{x}) = \sum_{i=1}^{N} \nabla^2 e_i(\vec{x}) \quad (9)$$

For the Gauss-Newton method it's assumed that S and equation (5) becomes:

$$\Delta \vec{x} = [J^T(\vec{x})\,J(\vec{x})]^{-1} J(\vec{x})\vec{e}(\vec{x}) \quad (10)$$

The Levenberg-Marquardt modification to Gauss-Newton method is:

$$\Delta \vec{x} = \left[J^T(\vec{x}) J(\vec{x}) + \mu I\right]^{-1} J(\vec{x})\vec{e}(\vec{x}) \quad (11)$$

The parameter μ is multiplied by some factor (β) whenever a step would result in an increased. When a step reduces, μ is divided by β. When the scalar μ is very large the L-M algorithm approximates the steepest descent method. However, when μ is small, it's same as Gauss-Newton method. Since minimum, the goal is to shift toward the Gauss-Newton method as quickly as possible. The value of μ decreased after each step unless the change in error is positive; i.e. the error increases. For the neural network-mapping problem, the terms in the Jacobian matrix can be computed by a simple modification to BP algorithm [30; 38].

III. MATERIALS AND METHODS

A. Localisation and morphologic characteristics of Tiagba's lagoon-bay

Known for its traditional houses built on stilts, Tiagba is Lake Village. It's one of tourist attraction of Côte d'Ivoire. Its lagoon bay is located in the far-west of Ebrié system (4°40' and 4°45' longitude west and 5°20' latitude north). It's large (11.5 Km^2), shallow lagoon (2.9 m about), with water volume estimated at 3.35 104 m^3. Its catchment basin is about 135 Km^2. This bay communicates with waters of the principal branch of Ebrié system's by the pass of "eaux libres du chenal central" and with the Cosrou's lagoon-bay by the pass of "Cosrou". Tiagba's lagoon bay is far from Vridi channel (80 Km), single entrance of sea-water in the system Ebrié. So, it undergoes little sea influence. The tides are very low with currents rarely exceeding 0.1 to 0.2 $m.s^{-1}$ [39]. So its renewal rate is linked to rainfall (meteorite runoff and fluvial contribution). On that coastline of Côte d'Ivoire, the climate is characterized by a long and short rainy-season (respectively in May-July and October), and a long and short dry season (respectively in December-April and August). The direct contributions of meteorite runoff waters are important in rainy-seasons. Water stream contributions essentially provide on the one hand from the river Bandama, characterized by an annual flood (from September to October) and pours into Grand-Lahou's lagoon (a tiny part reaches Tiagba's lagoon-bay through the channel of Assagny), and on the other hand from the river Ira, located in the coastline area and characterized by annual floods (the first and most important in June and the second in October). It pours in the Cosrou's lagoon bay through which, it reaches the Tiagba's lagoon-bay during the annual floods. Tiagba's lagoon bay is bad renewal. That's due to the small area of the coastline of the river Ira and low contribution in water of the river Bandama. The anthropogenic activities of its coastlines are dominated by agriculture. This bay receives domestic and agricultural wastes because of the sanitation lack systems on the drainage basin. Yao et al. [33] have shown that this system was a hypereutrophic lagoon.

B. Using of MLP-BP based on L-M algorithm in this study

1) Inputs and output variables

Concerning the prediction of the static evolution of chlorophyll a, 10 physicochemical parameters, important in the spatiotemporal evolution of the phytoplankton in this lagoon-bay (Temperature (T), pH (pH), Dissolved oxygen (DO), bio-carbonates (NH_4^+, NO_3^- and PO_4^{3-}), monthly precipitations (MP), monthly debit of the river Bandama (DBan) and shown his high presence in water bodies (suspended matters (SM), transparence (Trans)), was used as input variables. At these parameters, the Date of Sampling (DS) was added as input variable in the case of the prediction of the dynamic evolution of chlorophyll a in this bay. Chlorophyll a (Chl a) is constituted the only output variable in both cases.

2) Training and test processes

In this study, the development of MLP-BP based on L-M algorithm was performed by using the module TOOLBOX of MATLAB R 2008 software. Weights were initialized and were assigned randomly based on an input random number. As training progress, weights were modified to minimize the error in the output. The network architecture was optimized by the variation of the hidden neurons number to 1 at 15 using simple trial-and-error method. 1500 simulations were performed for each hidden neuron number and the best result was recorded. All throughout these simulations, the adaptive learning rates were used to speed up training. The learning rate was started at 0.2 and finally reducing to 0.01 whereas the momentum was fixed at 0.5.

Data used in this study were collected monthly during two years (August 2007-July 2009). Data set for prediction of the static evolution of chlorophyll a, composed of 4488 records, was coded between range [0; 22], while the one for prediction of the dynamic evolution of chlorophyll a composed of 5148 records was coded between range [0; 23]. Each of these sets was divided in two subsets. The first subset contained 75% of the records was used as a training set and the second contained 25% of the records as test set.

3) Validation of the optimal model

The choice of the optimal model was made based on the values of the training coefficient of determination (R^2tr), the test coefficient of determination (R^2te) and the mean squad error (MSE) during training process. The optimal model is the one that presents simultaneously high values of R^2tr and R^2te. In addition, it is possible that both models have similar performance in terms of coefficient of determination. In this case, the best performing model is one that has the lowest value of MSE. A model can be validated when its R^2te is superior to 0.5 [40-41] and all the values of MSE obtained during test process, are weak and perfectibility disturbed following the normal law according to Henry's representation [42-43].

IV. RESULTS

A. Spatial variation of the input data

The basic statistical parameters, i.e. minimum (Min), median, maximum (Max), mean, standard deviation (SD), and relative standard deviation (RSD) of the variables (Temperature (T), pH, dissolved oxygen (DO), NH_4^+, $NO_3^-$and PO_4^{3-}, monthly precipitation (MP), monthly debit of river Bandama (DBan), suspended matters (SM), transparence (Trans)) used in this study were presented in Table 1. PO_4^{3-}, DBan, SM, MP, NH_4^+, NO_3^- showed large spatial variations with RSD superior to 60%.

Factor	T	pH	Trans	DO	SM	NO_3^-	MP	DBan	NH_4^+	PO_4^{3-}
Mean	29,78	8,17	0,66	6,27	21,76	0,22	121,46	156,76	0,10	0,12
Max	32,90	9,97	1,00	11,98	186,00	1,63	357,70	412,18	0,96	1,18
Min	25,60	5,86	0,45	0,00	2,00	0,00	1,00	77,26	0,00	0,00
SD	1,65	0,84	0,11	2,68	24,37	0,26	99,93	115,37	0,14	0,16
Median	30,05	8,23	0,60	6,80	15,73	0,13	103,10	99,35	0,05	0,07
RSD	0,06	0,10	0,17	0,43	1,12	1,17	0,82	0,74	1,38	1,35

Table.1. Statistics of the variables studied (SD means standard deviation; RSD means Relative Square Deviation)

B. ANN architecture optimization

The determination of the most powerful architecture based on mean square error (MSE), coefficient of determination (R^2tr and R^2te) is a key step. Table 2 illustrates the performance studies for various topologies. The best compromise (that gave a low value of MSE, a high value of R^2tr and R^2te) was obtained respectively with the 10 – 11 – 1 and 11 – 11 – 1 structure ANN model. The network topology for these two models is shown in Fig.2 and Fig.3 respectively.

	Static study			Dynamic study		
Hidden neurons number	R^2_{tr}	R^2_{te}	MSE	R^2_{tr}	R^2_{te}	MSE
1	0,546	0,574	0,073	0,543	0,508	0,051
2	0,644	0,624	0,058	0,624	0,570	0,052
3	0,618	0,562	0,053	0,643	0,585	0,024
4	0,643	0,572	0,096	0,661	0,569	0,051
5	0,645	0,588	0,054	0,656	0,602	0,030
6	0,642	0,572	0,056	0,686	0,624	0,019
7	0,633	0,576	0,047	0,677	0,664	0,014
8	0,654	0,613	0,054	0,658	0,629	0,021
9	0,643	0,581	0,086	0,683	0,621	0,010
10	0,650	0,543	0,103	0,693	0,606	0,036
11	**0,647**	**0,626**	**0,059**	**0,698**	**0,664**	**0,019**
12	0,678	0,605	0,145	0,662	0,616	0,012
13	0,642	0,566	0,134	0,679	0,628	0,028
14	0,647	0,637	0,127	0,666	0,660	0,011
15	0,636	0,586	0,097	0,674	0,666	0,011

Table.2.Variation of R^2tr, R^2te and MSE as a function of hidden neurons number

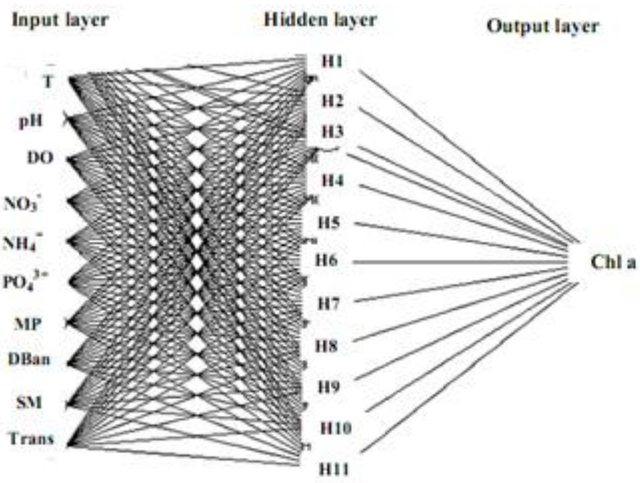


Fig. 2. Architectural network of the static model 10-11-1

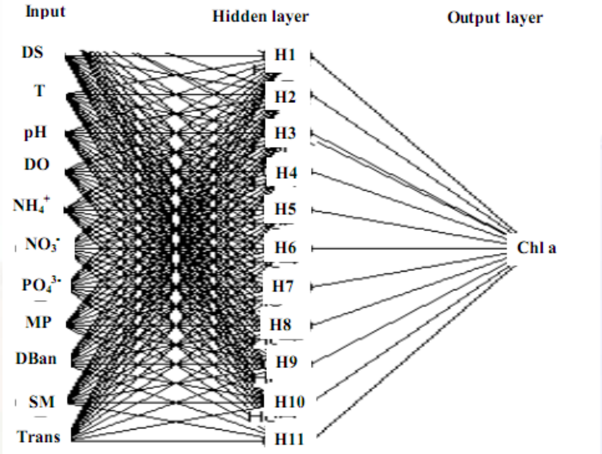


Fig. 3. Architectural network of model 11-11-1

C. Models validation

The static and dynamic model obtained respectively from architecture 10-11-1 and 11-11-1 were diagnosed using error analysis and normal unit of Residual plot (Henry's representation) depicted respectively in fig. 4 and 5. The scattered error plot showed that errors were uniformly and randomly distributed around the mean value (0) in the range of - 0.397 to 0.323 % for static model (Fig. 4A) and -0,384 to 0.278 for dynamic model (Fig. 4B). Moreover, while considering Fig.5A and 5B, the MSE were perfectively disturbed following a normal law with determination coefficient equal to 0,962. Consequently, the models obtained from the two architectures were suitable to be used for Chlorophyll a prevision and eutrophication monitoring.

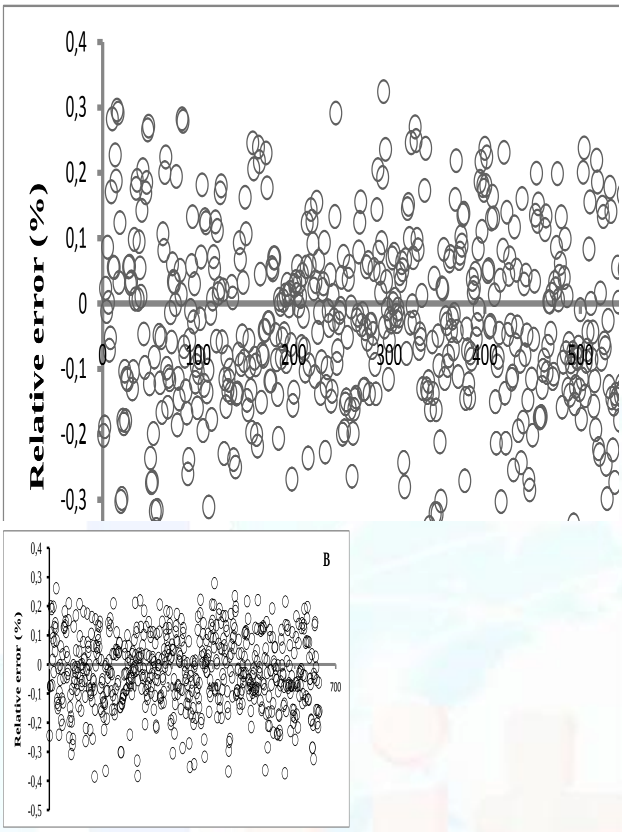
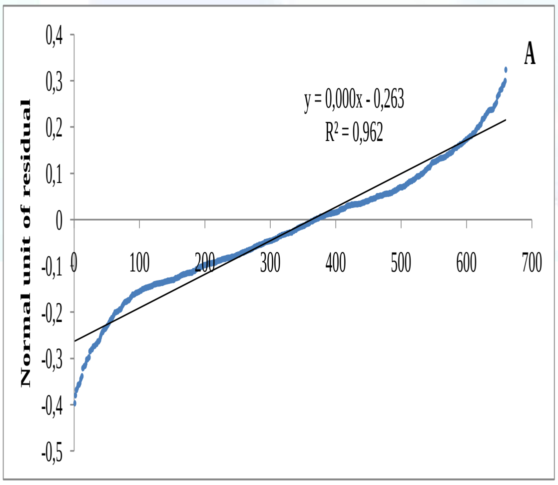


Fig. 4. Scatter error plot between observed and calculated outputs.



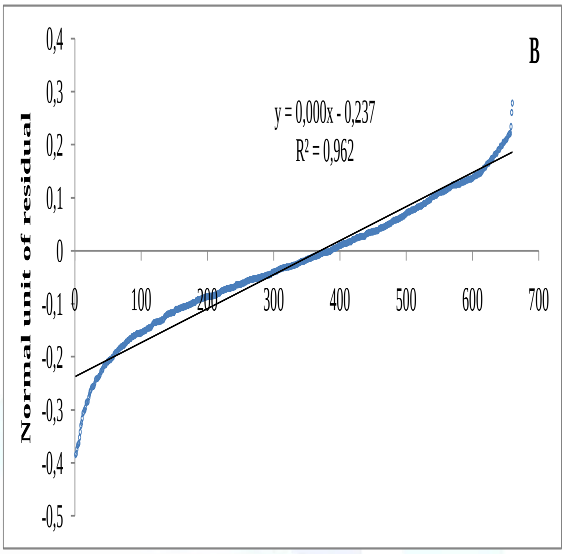


Fig.5. Normal unit plot of residual

V. Discussions

More closely looking at Fig.4 and 5, the MLP-BP based on L-M. Algorithm reproduce the observation well. So, the ability of this ANN model for eutrophication prediction is confirmed again in this work. Indeed, the model 10-11-1 traduces physically 80% (R^2tr = 0.647)$^{1/2}$ of the static evolution of chlorophyll a due to the variations of 10 inputs variables and predicts formally this evolution at 79% (R^2te = 0.626)$^{1/2}$ on the study period. Concerning the dynamic evolution of chlorophyll a, the model 11-11-1 express physically at 83.66% (R^2tr = 0.698)$^{1/2}$ the dynamic evolution of chlorophyll a due to the variations of 11 variables and predicts formally this evolution at 81.24% (R^2te = 0.664)$^{1/2}$ in the same period. The model obtained in the case of the dynamic study seems to be more suitable than the static one.

In addition the very weak relative error between observed and calculated outputs (Fig.4) is due for the best chosen of the factors (variables) affected the chlorophyll a evolution in this lagoon bay during the study period and by taken much care during training and validation process. In effect, a number of researchers have noted that their ANN models have failed to capture values which lie outside range of values contained in the ANN calibration data [44].

Finally, it's important to retain that study confirms ANN abilities to predict any complexes phenomenon such as eutrophication; as shown by many studies [30; 45-53].

VI. Conclusion

In this study, the ability of the ANN model to predict eutrophication in the lagoon bay of Tiagba in Côte d'Ivoire was investigated and justified. As for the ANN performance, the topology with 10 inputs and 11 hidden nodes gave the best performance in the case of the prediction of the static evolution of chlorophyll a while the topology with 11 inputs and 11 hidden nodes is the best for the prediction of the dynamic evolution of chlorophyll a. These models established give a good approach of the spatiotemporal variation of chlorophyll a in this lagoon bay and can be used for the eutrophication monitoring in the perspective of its rehabilitation and protection

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