PLANTAIN TREE GROWTH (MUSA SP., AAB CULTIVAR HORN 1) MODELING USING THE ARTIFICIAL NEURAL NETWORKS METHOD

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Abstract

The plantain tree growth is made up of a number of growth parameters such as leaves number (Ln), leaf length (Ll), leaf width (Lw), pseudo-stem height (Hp), width at 10 cm above the ground (W10), pseudo-stem width at middle (Wm) and its width at top (Wt). A study of these growth parameters was carried out in the area of Azaguié (Côte d'Ivoire). The results show that plantain tree growth depends on growth parameters evolution. For this purpose, mathematical models were developed to predict the growth using an artificial neural network. Satisfactory results were obtained since all the determination coefficients were higher than 0.97. These coefficients are approximately 1, and it points out the ability of the artificial neural network to map suitably the experimental data.

Keywords: Plantain tree, growth parameters, modeling, artificial neural networks

Introduction

Plantain tree plays a key role in the world in terms of food security, as it is the fourth most important harvest fruit in the world (Lassoudiere, 2007). It is originating from South Asia and is cultivated in more than 120 countries around the world (Jones, 2000). The banana production in the world is estimated at 102.687 million tons with 40 million for plantain in

2003 (Anonymous 1, 2003). In Africa, particularly in Côte d'Ivoire, plantain is regarded as an important local consumption (Yao, 1988). It is a good source of income and also provides employment opportunities and export revenue (Foure and Tezenas, 2000). In Côte d'Ivoire, with an estimated annual production of 1.42 million tons, plantain ranks third in the production of food apart from yam and cassava (Ducroquet, 2002; Anonymous 2, 2005).

From fruits to pseudo-stem via leaves, banana tree plays a key role in food and phytotherapy (Rabbani, *et al*., 2001). Banana is divided into two sub-groups: plantain fruits eaten after cooking (Horn, French) and those dessert type which are eaten raw (Anno, 1981). Dessert banana has long held the first place in literature due to its exportation to developed countries (Mc Niel, 1995). However, plantains which are common in many countries of the world play a key role at the nutritional and socio-economic levels (Valmayor, 1976; Anno, 1981).

Current research on plantain, are mostly related to viral diseases and to plant description (Lassoudiere, 1978; Anno, 1981). The growth of vegetative and reproductive units has been studied in detail for many years. However, the models include mechanisms of performance development (Jannoyer, 1995), fruits formation and maturation (Julien, 2000), root growth system (Leconte, 2002) or cropping (Tixier, 2004). Despite these recent findings, models developed on the growth of this plant are particularly scarce. Therefore, this study is focused on the modeling of plantain tree growth. From a mathematical viewpoint, the empirical model or "black box" model which uses the artificial neural networks was used for this purpose. Therefore, this approach is used to test the ability of this method to map suitably the experimental results of the parameters involved in growth of plantain tree.

1. Materiel And Methods
1.1 Biological material
The biological material used in the study was composed of tree plantain cultivars (*Musa* AAB cv Horn 1) shoot-scales which are grown majorly in Côte d'Ivoire. These shoots are reproduction and survival elements of plantain tree (Anno 1981). Thus, the shoot-scales were buds at a reduced leaf stage to the midrib and wound up on themselves, with no differentiated lamina. There are two categories of shoot-scales according to their insertion point on the parental underground rhizome (Anno, 1981; Turquin, 1998). The type "a" which is superficial, and the type "b" which is deeply inserted to the ground. Because of their high frequency and their good performance in the field (Turquin, 1998), only "b" type shoot-scales were used for this experiments.

1.2 Study Areas

The plantain tree growth modeling was conducted using two steps: an experimental one to measure growth parameters and the data processing step. The former step was carried out at Azaguié located in the southern of Côte d'Ivoire, within the CNRA research station at Bimbresso. The data was processed at Felix Houphouet Boigny Polytechnic Institute of Yamoussoukro; more precisely at the department of Food Science and Technology.

1.3 Plant material preparation

The sampling took place in the morning at fresh hours. Shoots were carefully removed to reduce the wound risk. This was followed by "trimming" the plant material involves cleaning the shoot in order to remove earthy particles, cut off all roots and remove all necrotic parts, rinse abundantly with tap water and lay them on absorbing paper for 10 minutes so as to eliminate flushing water (Sery, 2004). The shoots were finally weighed and measured (rhizome collar size, rhizome diameter and shoot length). These measurements were used to gather shoots of close weight to avoid field's heterogeneity. Thus, shoots weight according to Turquin (1998), must vary from 300 g to 500 g.

1.4 Fertilization and pesticide treatments

The fertilizers and herbicides used were inspired from the program developed by Lassoudiere (1978) (Table I).

1.5 Experimental methods

The experimental plot was 800 m^2 which has 150 plantain trees. A distance of 2.5 m between rows and 2.5 m between trees was constructed (Figure 1). All shoots were planted in holes of 40 x 40 x 40 cm (Sebuwufu *et al*., 2005).
A systematic monthly treatment against Sigatoka disease was carried out from the second month and observations were made on the vegetative unit. This treatment and observation started after one month of cultivation and were completed at the flowering period.

1.6 Measurement and growth assessment and development

The growth and development of plantain tree can be appreciated by two parameters, namely: the growth parameters and the development parameters.These parameters were those measured by Anno (1981) and Herrera *et al*. (2003). Leaves growth study was performed by measuring the length and width of the leaves. Whereas, leaves length (Ll) was taken from limb base to precursor filament one, and the leaves width (Lw) was taken at

the largest level of leaves width. Concerning the pseudo-stem, their height and circumference were measured; thus, the former parameter was measured from 10 cm above the ground (H10) to the plant top, at the V formed by the two last functional leaves. The circumference was measured at 10 cm (C10) above the ground, in the middle of the pseudo-stem (Cm) and at the top (Ct) at the V level, due to the fact that the pseudo-stem is not cylindrical. Therefore, all these measurements were performed weekly and were expressed in centimeters. Also, the plantain tree development was assessed by the number of leaves emitted (Nl) during the period of this experiment.

Table I: Fertilization program and pesticide treatments

Plantain tree age	Nitrogen fertilization (Urea) by g / plant	Potassium fertilization (KCl) by g / plant	Nematicides and insecticides by g / plant
3 weeks	25	--------	---------
1 month and 15 days	25	40	---------
2 months	40	40	30
3 months	40	50	---------
4 months	40	50	----------
5 months	40	50	30
6 months	--------	50	---------
7 months	40	100	----------
8 months	40	100	30
9 months	40	--------	---------
10 months	50	50	-----------

Source : LASSOUDIERE (1978) (Modified)

Figure 1: Experimental field

1.7 Modeling the growth of plantain by the artificial neural network

The plantain tree growth modeling was conducted using the artificial neural network method which was programmed in Matlab R2007b software (MathWorks Inc., Massachusetts, USA).

1.7.1 Artificial neural network structure

In this study, the basic architecture used was the multilayer perceptron (MLP) with three types of layers; namely: input, hidden and output ones. The network used herein is characterised by 7 neurons in the input and output layers. Thus, the neurons number in the hidden layer was varied from 1 to 15 so as to reach an optimal architecture.

1.7.2 Performance prediction models developed

The models obtained were used to predict the plantain tree growth. The suitability of fitting was appreciated via the determination coefficient (R^2). This coefficient measures the adjustment quality of the regression equation estimation. When R^2 is close to 1 in the case of a simple regression, the adjustment between the experimental and predicted values is better (Feinberg, 1996). This coefficient (R^2) is expressed as following:

$$R^2 = \frac{\sum_{i=1}^{N}\left(y_{préd} - \overline{y_e}\right)^2}{\sum_{i=1}^{N}\left(y_{préd} - \overline{y_e}\right)^2} \qquad (1)$$

With:

y_e and y_{pred} respectively, the experimental and calculated values for i = 1, ..., N;

and $\overline{y_e}$ is the means of the measured or experimental values.

Another approach is to determine the Bayesian Information Criterion of Schwarz (BIC) (Schwarz, 1978). The BIC is obtained as follows:

$$BIC = \log\left(\frac{V}{n}\right) + p\frac{\log(n)}{n} \qquad (2)$$

Where V is the approximate sum of squared errors, n is the number of training observations (50% of observations) and P is the total number of network weights.

2. Results
2.1 Analysis of different experimental measurements by the PCA

The experimental data on the growth parameters were subjected to a Principal Component Analysis (PCA) and the result obtained is plotted in figure 2. It is observed that by analyzing this figure, the origin variables are very correlated, which is the reason why the two first factors obtained after

PCA analysis represents a high level information (85.97 + 6.83 %). Moreover, the scatter plot points out two outliners data (encircled in the figure). Thus, these data were removed from the data base prior to modeling.

2.2 Plantain tree growth modeling by artificial neural networks
2.2.1 Architecture of the neural network

Table II shows the correlation coefficients (R) during training and validation steps. The analysis of this table shows that the correlation coefficients (R) of leaves number; for example ranging from 0.921 to 0.986 for the training step and from 0.771 to 0.994 for the validation one. By considering all the responses, the correlation coefficients (R) evolve in the same order, from (0.771 to 0.996) for all phases (training and validation). It is noticeable that the best R values are obtained for the circumference at 10 cm above the ground with 0.979 to 0.994 and the bad values are observed for the circumference at the top (0.919 to 0.843). Taking into account R value closer to 1 regarding training and validation phases, it is very difficult to determine the most efficient neural architecture. Indeed, in this case, the best architectures of neural network are: 7-4-7; 7-9-7 and 7-13-7. What is then the suitable artificial neural network topology that models the data provided? To answer this question, another approach is to calculate the BIC. Figure 3 shows the evolution of mean BIC calculated according to hidden neurons number. The BIC values vary from 4.444 to 6.420. While the lowest BIC is obtained for the topology 7-2-7, the highest one corresponds to the architecture 7-4-7; 7-9-7 and 7-13-7.

Therefore, when combining all the performance criteria of the network (i.e. R and BIC), the neural architecture which is the best compromise (taking into account the low BIC and R closer to 1) is the 7-2-7 topology. This topology consists of 7 neurons in the input layer, 2 neurons in hidden one and 7 neurons in the output layer.

Table II: Correlation coefficients (R) during the training and validation phase

Neurals of hidden layer	Correlation coefficients (Training phase)						
	Nl	Ll	Lw	Hp	C10	Cm	Ct
1	0.956	0.874	0.875	0.972	0.980	0.976	0.844
2	**0.954**	**0.979**	**0.983**	**0.996**	**0.980**	**0.985**	**0.947**
3	0.981	0.943	0.952	0.990	0.980	0.976	0.907
4	0.981	0.957	0.959	0.990	0.983	0.983	0.898
5	0.979	0.956	0.953	0.995	0.982	0.978	0.904
6	0.984	0.960	0.956	0.993	0.993	0.988	0.902
7	0.982	0.954	0.956	0.992	0.993	0.987	0.901
8	0.986	0.956	0.955	0.991	0.990	0.987	0.906
9	0.985	0.964	0.963	0.994	0.991	0.988	0.905
10	0.981	0.966	0.960	0.995	0.990	0.987	0.905
11	0.982	0.962	0.957	0.994	0.994	0.987	0.907

12	0.922	0.957	0.958	0.995	0.986	0.987	0.902
13	0.977	0.964	0.964	0.995	0.993	0.988	0.906
14	0.983	0.955	0.954	0.995	0.986	0.984	0.907
15	0.984	0.954	0.955	0.994	0.990	0.987	0.919
Correlation coefficients (validation phase)							
1	0.963	0.861	0.856	0.972	0.987	0.973	0.853
2	**0.960**	**0.967**	**0.965**	**0.992**	**0.985**	**0.981**	**0.956**
3	0.989	0.939	0.938	0.992	0.986	0.971	0.910
4	0.992	0.962	0.950	0.992	0.989	0.978	0.902
5	0.978	0.948	0.936	0.995	0.988	0.969	0.906
6	0.989	0.955	0.938	0.994	0.993	0.986	0.906
7	0.970	0.944	0.942	0.992	0.994	0.984	0.906
8	0.994	0.947	0.938	0.992	0.991	0.983	0.909
9	0.991	0.955	0.952	0.995	0.992	0.985	0.898
10	0.979	0.953	0.941	0.995	0.990	0.984	0.896
11	0.983	0.959	0.943	0.994	0.994	0.984	0.903
12	0.772	0.937	0.941	0.997	0.986	0.980	0.880
13	0.964	0.946	0.952	0.994	0.992	0.985	0.863
14	0.985	0.949	0.936	0.996	0.988	0.980	0.901
15	0.988	0.940	0.942	0.993	0.991	0.982	0.915

Values in bold represent chosen correlation coefficients (R)
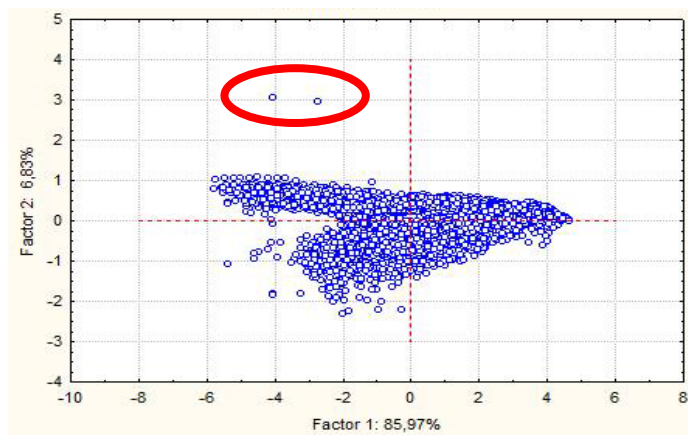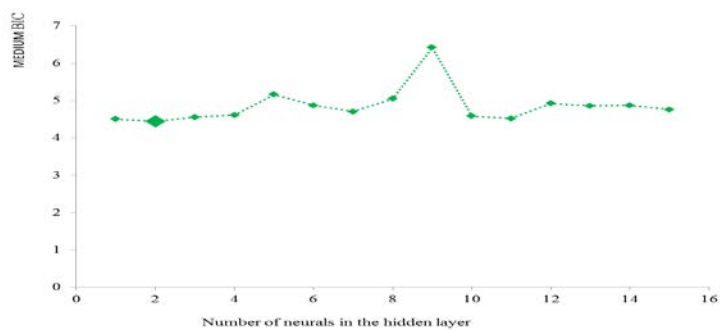

Figure 2: PCA plot of experimental data

Figure 3: Evolution of mean BIC according to hidden neurons in layer

2.2.2 Validation of the optimized neural architecture

After the determination of the optimized artificial neuronal network topology, the other phase is to validate it. Validation of the 7-2-7 neural network was performed via the determination coefficients (R^2) between the predicted values and experimental ones. This is done by plotting in the same figure these different values as presented in Figures 4 to 10. Analysing these figures, it appears that the determination coefficients (R^2) ranges from 0.9734 to 0.9976.Hence, all the values are above 0.97 is close to 1.

$y = 0.9223x + 2.7089$
$R^2 = 0.9924$
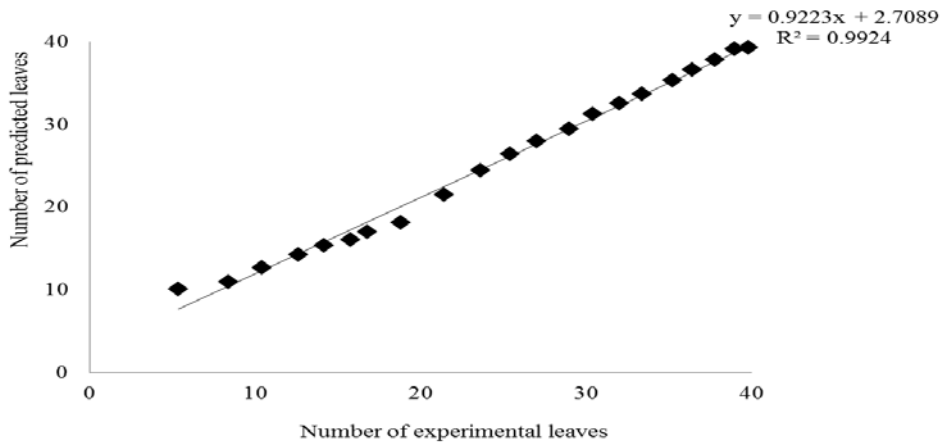
Figure 4: Regression curve between predicted and experimental values for leaves number

$y = 0.9682x + 0.9591$
$R^2 = 0.9911$
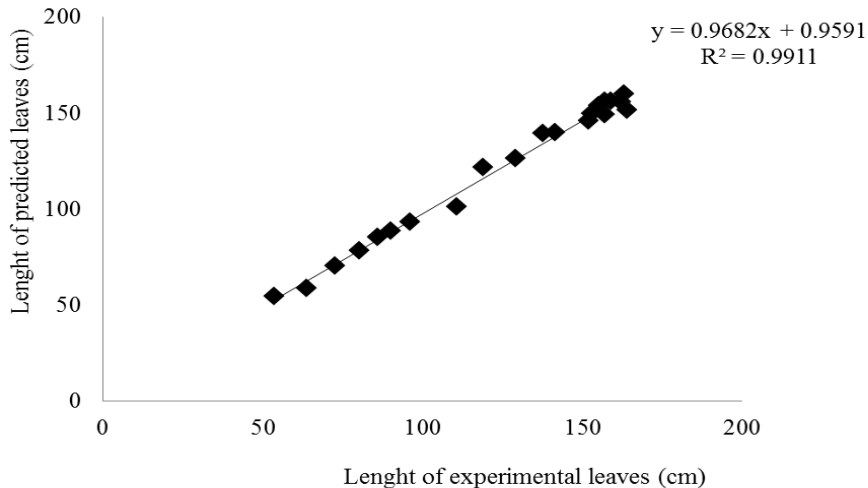
Figure 5: Regression curve between predicted and experimental values

$$y = 0.8841x + 7.316$$
$$R^2 = 0.9863$$
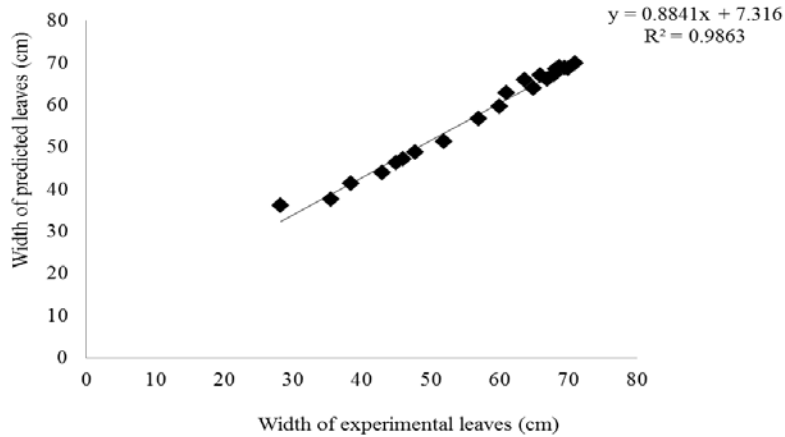
Figure 6: Regression curve between predicted and experimental values of leaves width

$$y = 0.9044x + 20.853$$
$$R^2 = 0.9976$$
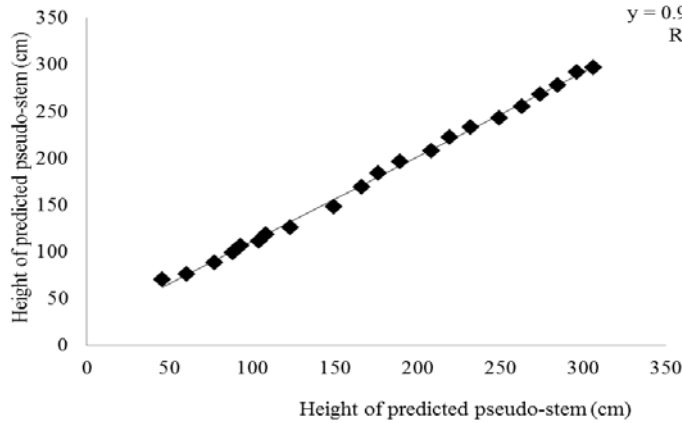
Figure 7: Regression curve between predicted and experimental values of pseudo-stem height
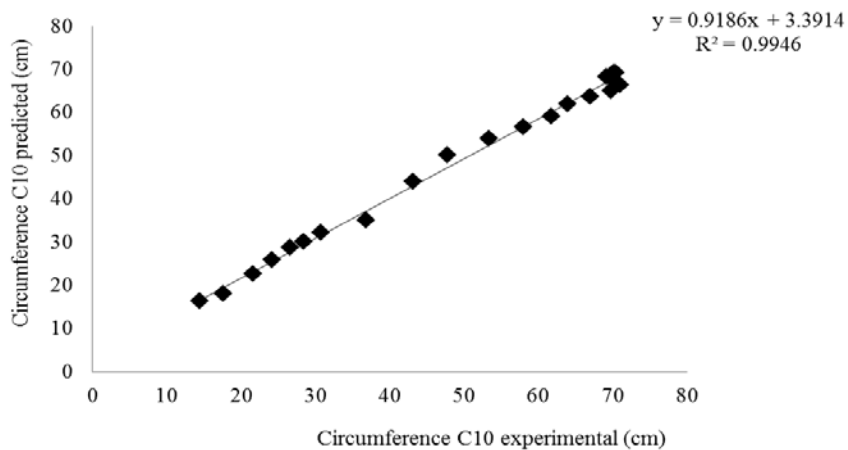

$$y = 0.9186x + 3.3914$$
$$R^2 = 0.9946$$

Figure 8: Regression curve between predicted and experimental values of the pseudo-stem circumference at 10 cm above the ground
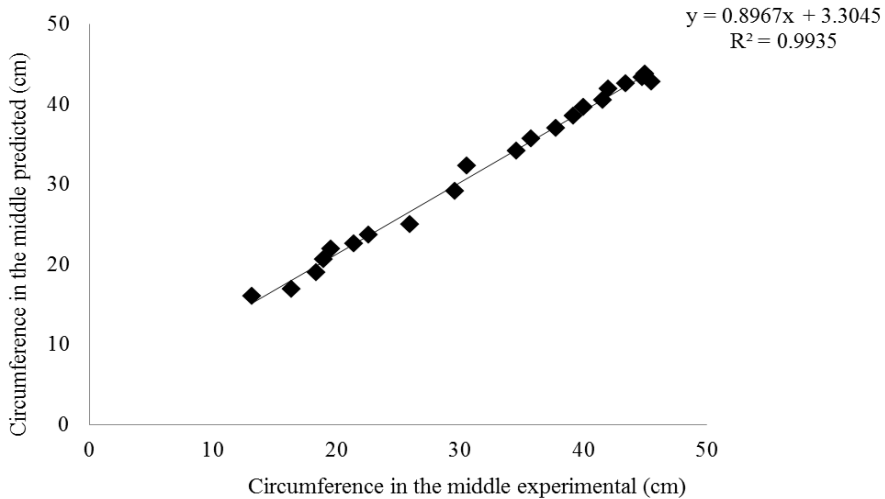
280

Figure 9: Regression curve between predicted and experimental values of the pseudo-stem circumference in the middle
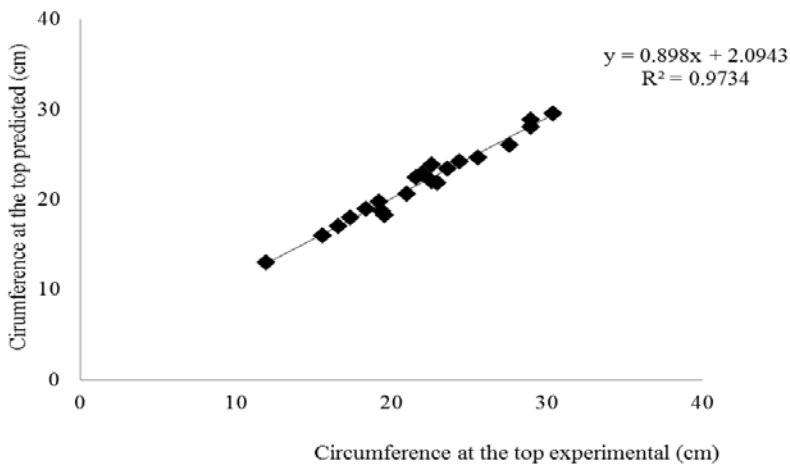

Figure 10: Regression curve between predicted and experimental values of the circumference at the top of the pseudo-stem

3. Discussion

The artificial neural network model selected is a compromise between the correlation coefficients (R) obtained during the training phase and those obtained during the validation phase (Chouai *et al*., 2000; Chevret, 2007). Considering all criteria including BIC, the 7-2-7 neural architecture (that is to say, seven input neurons, two in the hidden layer and 7 outputs)

was selected as the best topology and it was validated using data not used during the training phase.

Phenomena modeling using artificial neural network consist in finding, firstly, the appropriate topology of the network that enables proper mapping of the experimental data. This architecture is obtained when neurons number in the different layers (i.e. input, hidden and output) is determined; whereas the neurons number in input and output layers is the number of variables and responses respectively, that in hidden layer must be determined. Two approaches are generally used (Le Cun, 1990). In our study, this number was varied from 1 to 15. The 7-2-7 neural topology was found to be the best compromise between high correlation coefficient R values and low BIC ones. This artificial neural network model was tested using data not used during training and validation steps. The R value obtained shows the ability of the network model to map correctly the banana growth data. This artificial neural network ability in modeling purpose was pointed out in many studies. For example, the results are identical to those of Tixier (2004) in the case of the conception guided by model of sustainable cultivation systems: applied to banana tree systems of Guadeloupe. In the case of the conception of these models, that author has come to realize that some values of R^2 are higher than 0.95. Other authors like Julien (2000) and Jannover (1995) successfully used models which permitted them to obtain some R^2 higher than 0.95 as well. Assidjo *et al*. (2006) had successfully used an artificial neural network 4-4-4 topology to model an industrial scale brewing process. Chen and Ramaswamy (2002) and Mohamed (2007) also successfully used artificial neural network for thermal transfer and chemical reactions respectively in the food industry.

Therefore, our results once more confirm the ability of artificial neural network in general to make approximations dynamic phenomena such as plantain tree growth which has the capability to fully represent the non-linear complex relations.

Conclusion

The modeling was carried out by an empirical model using artificial neural network from experimental measurements taken in the field. It was made from the number of leaves (Nl), from the leaf length (Lf), from the leaf width (lw), the pseudo-stem height (Hp), from the circumference 10 cm above the ground, from the circumference to the middle of the pseudo stem and from the circumference at the top. Models using the artificial neural network as a tool have helped to successfully predict the growth of plantain tree from the above-mentioned operational variables. These models gave a narrow adequacy between the values of the experimental operational variables and those calculated by the network; thus it permits to satisfactorily

approach the growth of plantain tree. These models showed that the determination coefficients (R^2) is greater than 0.97. Thus, this shows the good performances of the artificial neural network to model the growth of plantain tree. However, the models achieved presents a slight differences. Finally, we noticed from this study that artificial neural networks are very good models for the simulation and prediction of plantain tree growth; thus, the models gives a very good performances.

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