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European Scientific Journal January 2015 edition vol.11, No.3 ISSN: 1857 – 7881 (Print) e - ISSN 1857- 7431

BATCH FERMENTATION PROCESS OF SORGHUM WORT MODELING BY ARTIFICIAL NEURAL NETWORK

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Abstract

The production of *tchapalo* (traditional beer) remains uncontrolled and artisanal. For the improvement of the product quality, we need to know more about the traditional process and beer characteristics. The fermentation process is one of the most critical steps, which determines the quality of the beer. In this study, artificial neural network, precisely multi layer perceptron was used for modeling batch fermentation process of sorghum wort. The artificial neural network showed its ability to predict the ph, temperature, substrate, biomass, carbon dioxide (CO_2) and alcohol (ethanol) evolution during batch fermentation of sorghum wort. All the correlation coefficients between the observed and predicted values for the artificial neural network were higher than 0.96. Thus, artificial neural network can be used to determine fermentation deviations during production of *tchapalo* and also to monitor and improve its quality.

Keywords: Batch fermentation, artificial neural network, modeling, sorghum wort, *tchapalo*

Introduction

Sorghum beer is a traditional alcoholic beverage produced and consumed in several african countries (Yao *et al*., 1995; Amané et *al*., 2005). The manufacture of this beer is handcrafted by traditional brewers using a number of raw materials that gives particular organoleptic characteristics. The sorghum, the clarifying, the traditional starter and the water constitute

the raw materials. Other sources of substrates like corn or millet can be used to substitute the sorghum (Kayode et *al*., 2005). This traditional beer has nutrient values (high starch proportions, protein, fat, vitamins and minerals) that improve the diet of consumers (Chistsika and Mudimbu, 1992). Therapeutic virtues such as laxative effects, antimalarial and anti hemorrhoidal were assigned to this beer. In addition, its relatively low price makes it accessible to all budgets (Enou, 1997).

In côte d'ivoire (Ivory Coast), the productions of this traditional sorghum beer by women need a stage of spontaneous lactic fermentation, followed by alcoholic one. The step of the alcoholic fermentation of the sorghum wort is done with traditional ferments generally selected from dried deposits of previous productions. This fermentation process lasts between 12 and 18 hours and usually leads to a *tchapalo* whose alcohol rate varies between 3 and 6% (v/v) (amane et *al*., 2005; dje et *al*., 2008; aka et *al*., 2008). Although the high amount of alcohol, the fermentation process still faces to many problems. Indeed, it takes place in deplorable hygienic conditions with the use of basic equipment and painful operations. The process is also, traditional and uncontrolled. Thus, beers produced have variable quality and vary from one production to another. In addition, they often have poor hygienic quality and cannot be stored for a relative long time. Therefore, huge losses of incomes are observed.

In order to provide solutions to problems encountered by these traditional brewers, several studies have been conducted. Earlier reports conducted by aka (2009) and n'guessan (2009) led to the selection of strains of lactic acid bacteria and yeast which could be used as starter cultures to accomplish respectively spontaneous lactic fermentation and alcoholic one. Those of Assidjo et *al*. (2009) concerned a hybrid neural network approach for batch fermentation simulation. These studies represent significant progress in controlling *tchapalo* production. However, in order to control *tchapalo* large-scale production, they should be complemented by predictive studies of the variability of physicochemical and microbiological parameters of batch fermentation. For this purpose, one of the most appropriate strategies for controlling these parameters is the use of artificial neural network. Indeed, the artificial neural network is a model (black-box) which proved to be non-linear universal approximators used to solve complex non-linear phenomena such as fermentation (Assidjo *et al*., 2006; Kouamé, 2010). This network concept is used for describing a particular type of model that emulates the human brain behavior.

The purpose of this work is to use the artificial neural network for modeling the batch fermentation process of the sorghum wort in real time, in order to control *tchapalo* large-scale production. It is expected that the

results obtained from the study will contribute in valorizing the traditional sorghum beer and serve as a guide for future research.

Materials and methods

Experimental systems

The neural network modeling technique was employed in batch fermentation in which, the yeast consume glucose to produce alcohol and carbon dioxide (co_2) (Assidjo *et al*., 2009). The fermentations were performed using a brunswick microferm fermentor (new brunswick scientific co inc., New Jersey, USA). Firstly, the wort was produced by crushing the malt into coarse flour that was then mixed with water (Amané, 2009). The resulting porridge like mash was heated to a selected temperature that permitted the malt enzymes to partially solubilize the ground malt. The resulting sugar-rich aqueous extract (wort), was separated from the solids and boiled. The wort was then clarified, cooled and poured in the vessel of the micro-fermentor for inoculation. Inoculated ferments were traditionally produced by female brewers that use it for a well-known local beer (*tchapalo* or *dolo*) making (Assidjo *et al*., 2009). This ferment is in fact a mixture of microorganisms containing different species (e.g. *Saccharomyces cerevisiae, candida* …). During the fermentation process (t=0 to 18 h), different parameters (ph, temperature, sugar rate (substrate), biomass, carbon dioxide and alcohol (ethanol)) were measured. The ph and temperature values of the sorghum wort (t = 0 to 18 hours of fermentation) were determined using a phmeter and a sterile thermometer (aspina 09654.40, france) incorporated directly into the brunswick microferm fermentor (New Brunswick scientific co inc., New Jersey, usa). The sugar rate (substrate) of sorghum wort was determined using a hand refractometer (mc 51295, france). Carbon dioxide (co_2) content of sorghum wort is determined using a co_2 gas analyzer incorporated into the micro-bioreactor. Alcohol rate (%) is determined after distillation and titration according to a method described by kouamé (2010). Biomass (microbial quantity) is quantified by the gravimetric method (Barbin, 2006).

Experimental values of these parameters obtained from the fermentation (t = 0 to 18 h) were used to build a representative scientific database. For the purpose of this study, 30 batches were performed.

Neural network creating and training

The neural network used to monitor the batch fermentation process of the sorghum wort was multi layer perceptron with one or two hidden layers. The multi layer perceptron was chosen because it seems to be the easiest to use and able to model any continuous function (Hornik, 1989). The activation function employed in the hidden layers was sigmoid (tanh)

function while for outer layer linear function was used. The number of the hidden neuron was firstly varied from 1 to 10. Backpropagation technique was used to train the net and, weights and biases were determined using levenberg-marquardt algorithm.

The database was constituted from measurements of physicochemical and microbiological parameters (explanatory or relevant parameters) obtained during the thirty essays of batch fermentation. The input and output variables concerned ph, temperature, substrate (sugar rate), biomass, carbon dioxide and alcohol (ethanol). About of 284 records were collected after filtering out the records that contained missing or spurious data. A number of 284 pairs of input/output data were computed. This data set was subdivided in 2 subsets training and validation (Kouamé, 2010). Before training process, data were all normalized in order that their values were in (-1, +1) range.

The optimal artificial neural network was that for which the lowest prediction error of the model was obtained. The prediction error was the mean square error (mse) defined as follows (Assidjo *et al*., 2009):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_e - y_c\right)^2 \quad (1)$$

With y_c and y_e the calculated and observed responses for i = 1, ..., *n*; *n*, the number of data.

Calculations for artificial neural network were implemented in matlab r2007b (Mathworks inc., Massachussets, USA).

Statistical methods

Correlation coefficient (r)

The correlation coefficient (r) is usually used to evaluate the performance of neural models. It is obtained by linear regression between the experimental and the predicted values from the network. When the absolute value of the correlation coefficient (r) between the experimental values and those predicted by the system approaches zero (0), the degree of binding is small. Its formulation is obtained as follows:

$$R = \frac{\sum_{i=1}^{N}\left(y_e - \overline{y_e}\right)\left(y_c - \overline{y_c}\right)}{\sqrt{\sum_{i=1}^{N}\left(y_e - \overline{y_e}\right)^2}\sqrt{\sum_{i=1}^{N}\left(y_c - \overline{y_c}\right)^2}} \quad (2)$$

With y_e and y_c the experimental and calculated values, $\overline{y_e}$ and $\overline{y_c}$ the means of experimental and calculated values respectively and *n* the number of variables.

Analysis of variance (anova)

Analysis of variance (anova) was used in addition to the mean square error (mse). It verifies the different architectural behaviors of artificial neural networks when they appear to be identical or confused considering the performance criteria. It involves two hypotheses (h_o null and alternative hypothesis h_1) (Feinberg, 1996; Assidjo et *al*., 1998). The choice of neural architectures is based on the coefficient calculated f1 (Fisher coefficient) which is compared to a threshold value played back (f) in the table of fisher (fisher test, $p < 0.05$). If the calculated value is less than the value played back from the table, the hypothesis h_o is saved.

Testing the least significant difference (lsd)

When the analyses of variance (anova) revealed significant differences, another method is needed to detect among the means, those that are equivalent. It is possible to use the least significant difference method (lsd). This method was used to determine differences between the architectural behaviors of artificial neural networks. The least significant difference was defined as follows (Feinberg, 1996):

$$LSD = \sqrt{\frac{2 \times V_r}{n}} \times t \qquad (3)$$

With *t* the student coefficient, *n* the number of runs and v_r the residual variance.

Results

Topology of artificial neural network

The number of the hidden neuron was varied from 1 to 10 and the comparisons between the performance of the different topologies were assessed. The regression line obtained from this comparison is characterized by its correlation coefficients (r). Table 1 presents the correlation coefficients of physicochemical and microbiological parameters depending on the number of neurons in hidden layer during the training and validation subsets.

Table 1: correlation coefficients of physicochemical and microbiological parameters depending on the number of neurons in hidden layer during the training and validation subsets

Nodes in hidden layer	Correlation coefficients (training)					
	Ph	Temperature	Substrate	Biomass	Co_2	Alcohol
1	0.051	0.608	0.857	0.515	0.961	0.865
2	0.913	0.628	0.940	0.734	0.983	0.866
3	0.958	0.899	0.981	0.836	0.982	0.959
4	0.996	0.981	0.987	0.964	0.984	0.961
5	0.998	0.981	0.988	0.970	0.992	0.978
6	**0.999**	**0.984**	**0.993**	**0.979**	**0.997**	**0.978**
7	0.998	0.982	0.991	0.972	0.996	0.981
8	0.998	0.984	0.993	0.978	0.996	0.983
9	0.998	0.990	0.993	0.976	0.995	0.986
10	0.998	0.990	0.994	0.977	0.997	0.986
	Correlation coefficients (validation)					
1	0.045	0.575	0.863	0.493	0.957	0.8 9
2	0.909	0.601	0.941	0.721	0.981	0.862
3	0.951	0.877	0.981	0.830	0.980	0.957
4	0.996	0.978	0.986	0.974	0.982	0.961
5	0.998	0.974	0.987	0.978	0.990	0.968
6	**0.998**	**0.986**	**0.993**	**0.987**	**0.996**	**0.970**
7	0.998	0.976	0.994	0.972	0.996	0.963
8	0.998	0.978	0.993	0.978	0.995	0.957
9	0.997	0.981	0.993	0.977	0.995	0.908
10	0.998	0.979	0.994	0.972	0.996	0.956

Underlined values correspond to the higher correlation coefficients (r)

Analysis of this table shows that correlation coefficients (r) values ranged from 0.045 to 0.999 for all responses. It was also observed that best correlation coefficients (r) values were obtained with 6 neurons in the hidden layer concerning training and validation phases. In addition, correlation coefficients (r) values are in all cases higher than 0.95 (very close to 1) when number of neurons in the hidden layer is superior or equal to 4. The network which can be retained, taking account all responses to predict fermentation parameters assessed is 6-6-6.

The ability of networks with two hidden layers was checked. For this purpose, the number of the hidden neuron (x) was varied from 1 to 10 and the best neural architectures were retained. Figure 1 shows the evolution of the mean square errors (mse) of these neural architectures. As shown in this figure, two parts can be distinguished while considering the number of neurons in the hidden layer. The first part of the curve showed that the mean squared error (mse) decreased widely across an initial value (0.492 to 0.544) to a limit one (0.034 to 0.110) until the fourth neuron in the hidden layer. The second part showed a stable evolution of the mean square error (mse)

around the limit values whatever the number of neurons in hidden layer. These curves seem confounded.

Anova test was done considering values from 5 to 10 neurons in hidden layer. The results are presented in table 2.

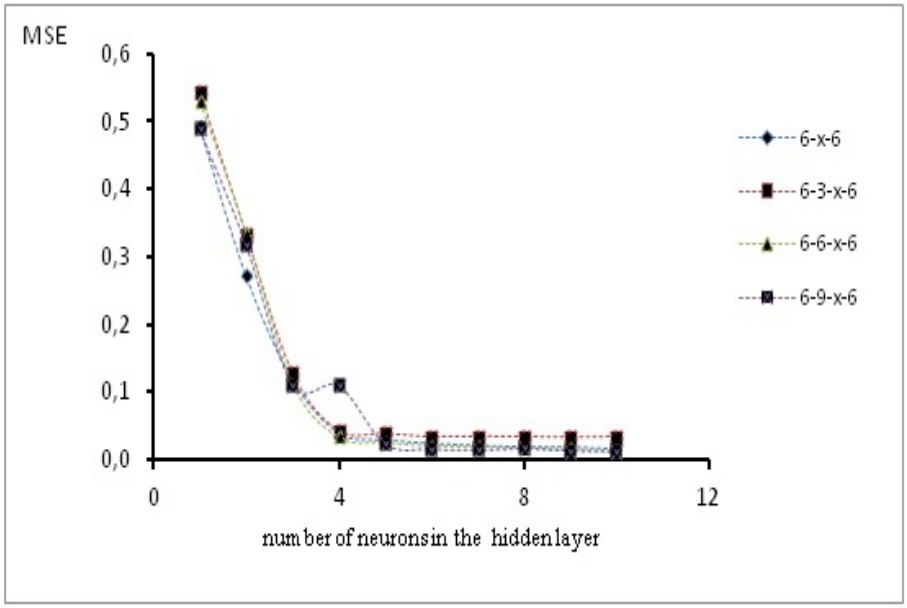


Figure 1: Evolution of the mean square error (mse) of different neural architectures

Table 2: Analysis of variance of the mse from different neural architectures

Source of variation	Degree of freedom	Sum of square	Variance	F1	Probability	F
Residual	3	0.001	0.000	25.05	0.000	2.96
Model	20	0.000	0.000			
Total	23	0.001				

F1: coefficient calculated

F: value played back in the table of fisher

As shown in this table, the calculated value of fisher coefficient (25.05) was higher than the tabulated (2.96) one. It was observed a significant difference ($p<0.05$) between behavior of the architectures.

A post-hoc test (fisher least significant difference lsd) was performed to determine between topologies those that have same performance. The results are presented in table 3.

Table 3: Test of the least significant difference of the mse from different neural architectures

Serie i	Serie j	Mean difference (i-j)	Probability
1	2	0.003	0.118
	3	**0.006**	0.005
	4	**-0.011**	0.000
2	1	-0.003	0.118
	3	0.003	0.147
	4	**-0.014**	0.000
3	1	**-0.006**	0.005
	2	-0.003	0.147
	4	**-0.018**	0.000
4	1	**0.011**	0.000
	2	**0.014**	0.000
	3	**0.018**	0.000

Mean difference is significant at $p \leq 0.05$
1: 6-x-6; 2: 6-6-x-6; 3: 6-9-x-6; 4: 6-3-x-6

It was observed that the behavior of neural architecture 6-3-x-6 differed significantly ($p< 0.05$) from the other ones. As shown in this table, the neural architectures 6-9-x-6 and 6-6-x-6 are equivalent and differ from the neural architecture 6-x-6.

The correlation coefficients (r) of the fermentation parameters for two hidden layers during the training and validation phases are presented in table 4. The results showed that the neural architecture 6-6-10-6 has the best correlation coefficients in the both phases (training and validation). This neural architecture has correlation coefficients (r) more close to the value one (1). Its topology includes 6 neurons in the input layer, 6 neurons in the first hidden layer, 10 neurons in the second hidden layer and 6 neurons in the output layer.

Table 4: Correlation coefficients of physicochemical and microbiological parameters depending on the number of neurons in two hidden layers during the training and validation phases

Network topology	**Correlation coefficients (training)**					
	Ph	**Temperature**	**Substrate**	**Biomass**	**Co_2**	**Alcohol**
6-3-3-6	0.991	0.847	0.986	0.817	0.985	0.962
6-3-6-6	0.996	0.978	0.985	0.970	0.989	0.978
6-6-3-6	0.958	0.908	0.981	0.845	0.983	0.967
6-6-6-6	0.997	0.989	0.992	0.978	0.994	0.985
6-6-10-6	**0.998**	**0.995**	**0.994**	**0.998**	**0.997**	**0.996**
6-9-3-6	0.897	0.881	0.864	0.983	0.971	0.922
6-9-6-6	0.992	0.993	0.984	0.995	0.988	0.994
6-9-10-6	0.995	0.994	0.987	0.985	0.992	0.988
	Correlation coefficients (validation)					
6-3-3-6	0.991	0.803	0.982	0.818	0.984	0.960
6-3-6-6	0.997	0.976	0.980	0.983	0.987	0.968

6-6-3-6	0.950	0.878	0.976	0.843	0.982	0.957
6-6-6-6	0.997	0.979	0.988	0.976	0.992	0.935
6-6-10-6	**0.998**	**0.989**	**0.998**	**0.980**	**0.997**	**0.986**
6-9-3-6	0.950	0.869	0.973	0.857	0.980	0.960
6-9-6-6	0.992	0.984	0.987	0.982	0.994	0.904
6-9-10-6	0.992	0.983	0.991	0.974	0.996	0.945

Underlined values correspond to the higher correlation coefficients (r)

Simulation by artificial neural network

The topology 6-6-10-6 is used to predict the values of the physicochemical and microbiological parameters. The validity of the model obtained is highlighted by figure 2, 3, 4, 5, 6 and 7, respectively for ph, temperature, substrate, carbon dioxide, biomass and alcohol evolution. The global analysis showed that the predicted values were close to the experimental ones.

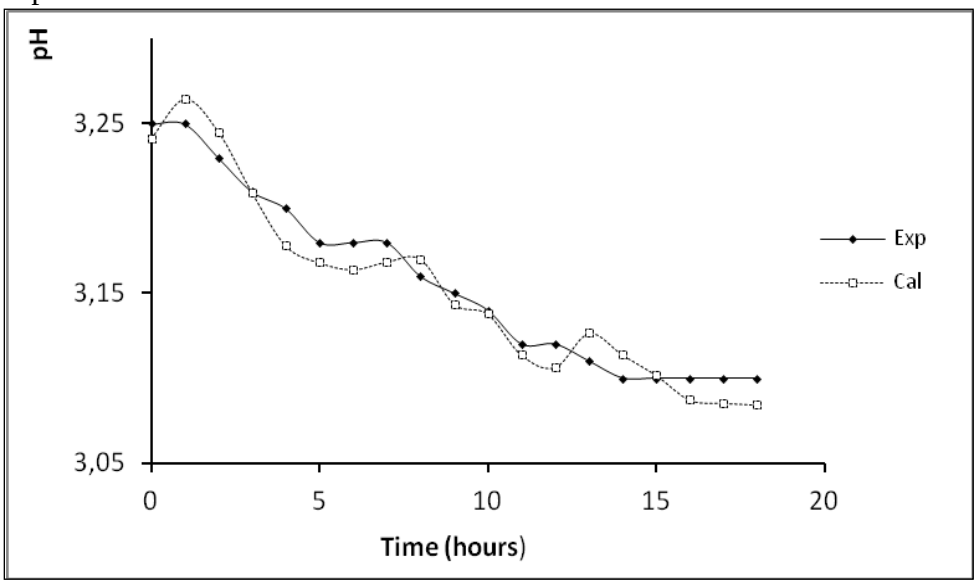


Figure 2: comparison between the evolution of experimental (exp) and predicted (cal) ph values during the time of batch fermentation

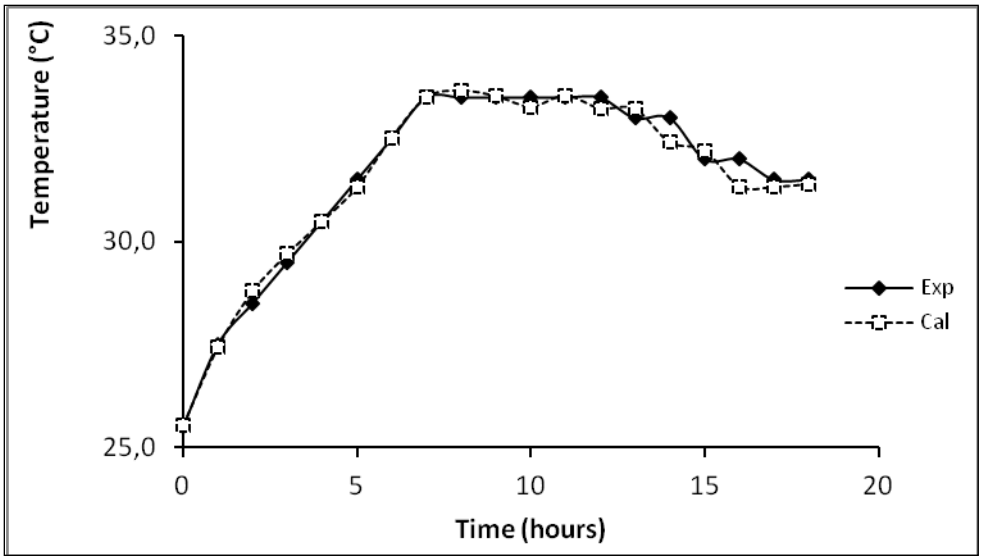


Figure 3: Comparison between the evolution of experimental (exp) and predicted (cal) temperature values during the time of batch fermentation

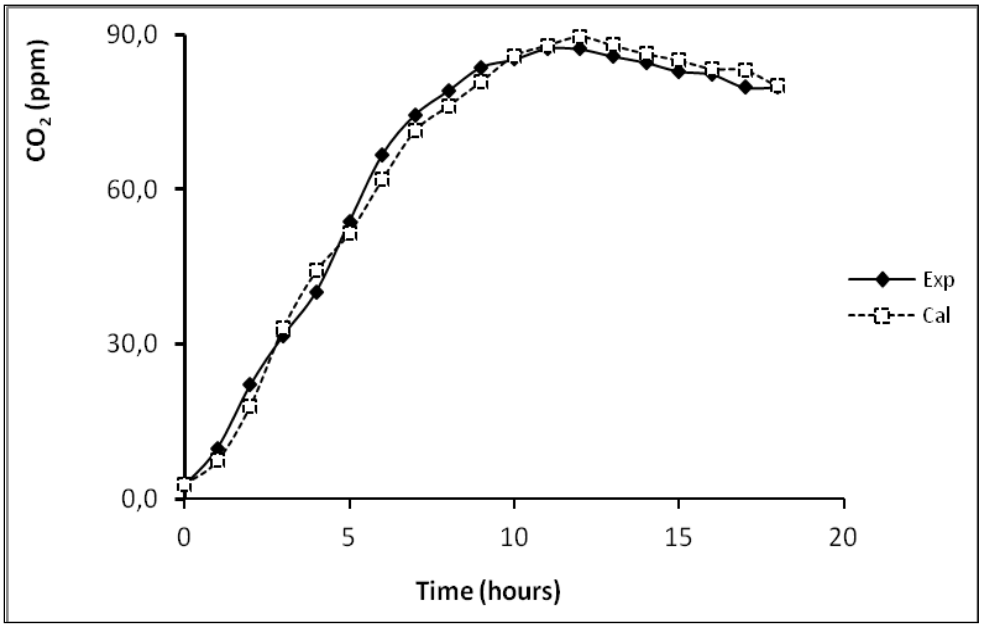


Figure 4: Comparison between the evolution of experimental (exp) and predicted (cal) co_2 values during the time of batch fermentation

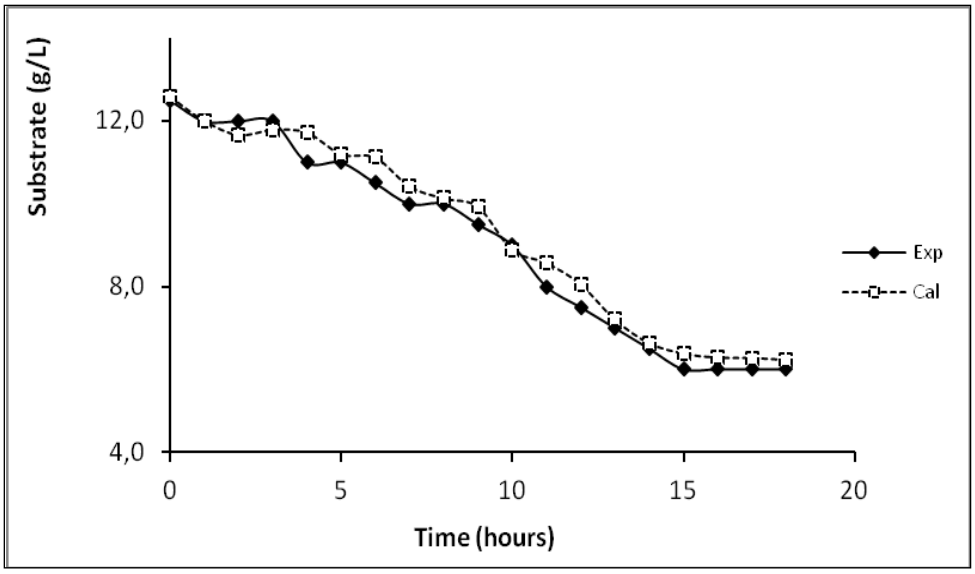


Figure 5: Comparison between the evolution of experimental (exp) and predicted (cal) substrate values during the time of batch fermentation

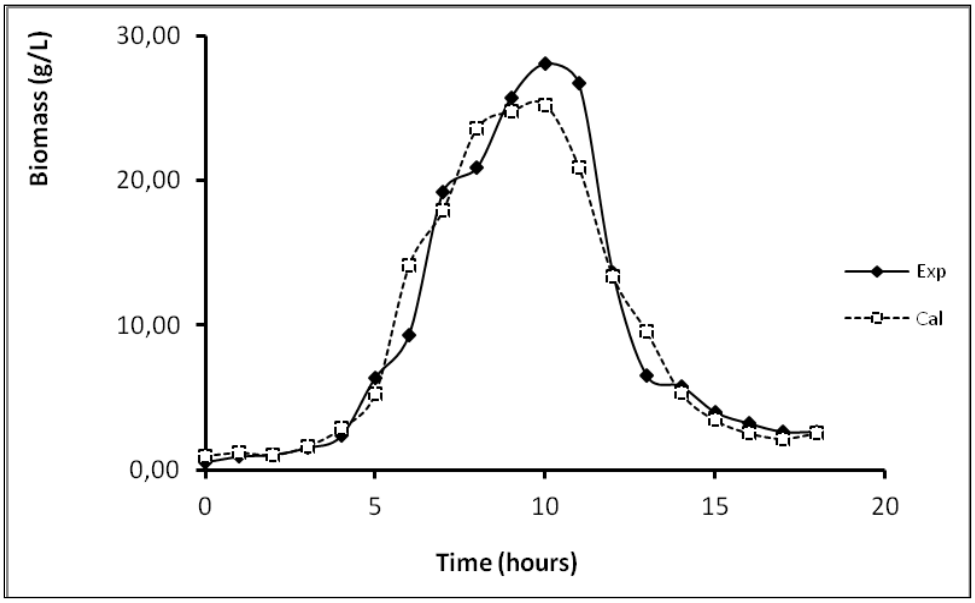


Figure 6: Comparison of experimental (exp) and predicted (cal) biomass evolution during the time of batch fermentation

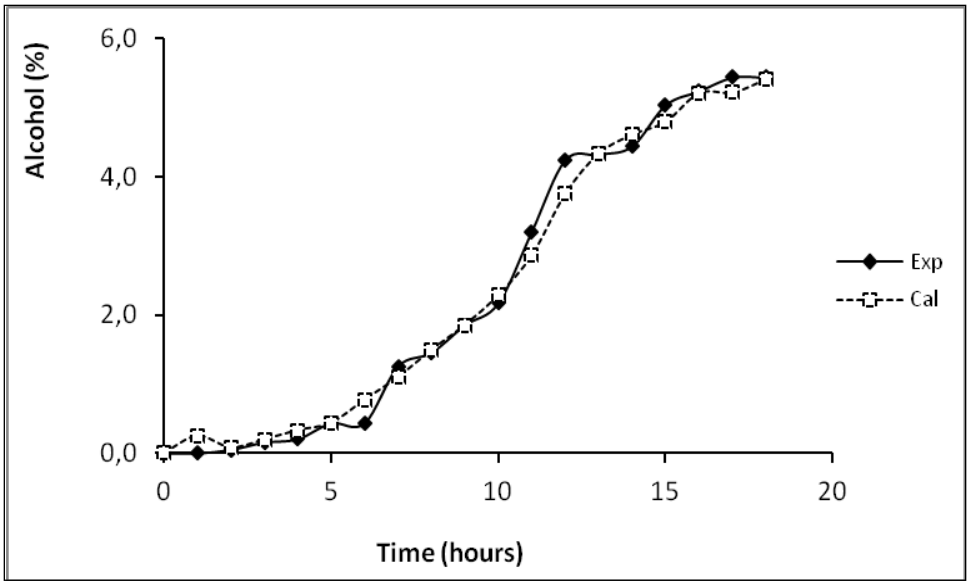


Figure 7: Comparison of experimental (exp) and predicted (cal) alcohol evolution during the time of batch fermentation

The regression line between the observed values and those predicted by the artificial neuron network topology 6-6-10-6 and the determination coefficients (r^2) are presented in figure 8, 9, 10, 11, 12 and 13, for ph, temperature, biomass, substrate, co_2, and alcohol respectively. It was observed that the determination coefficients varied from 0.950 to 0.992. All the determination coefficients recorded were above the value of 0.950.

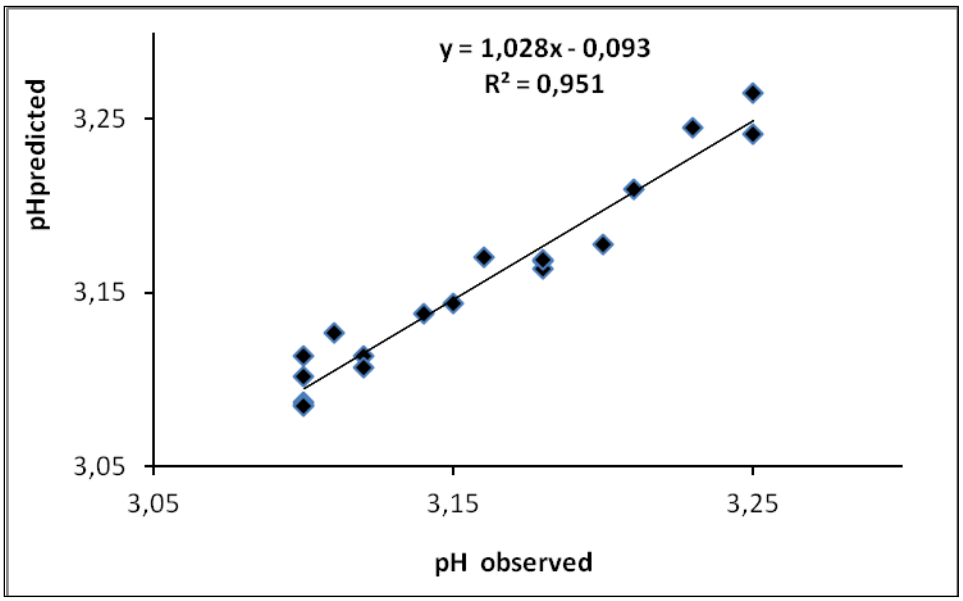


Figure 8: Regression curve between predicted and observed values for ph

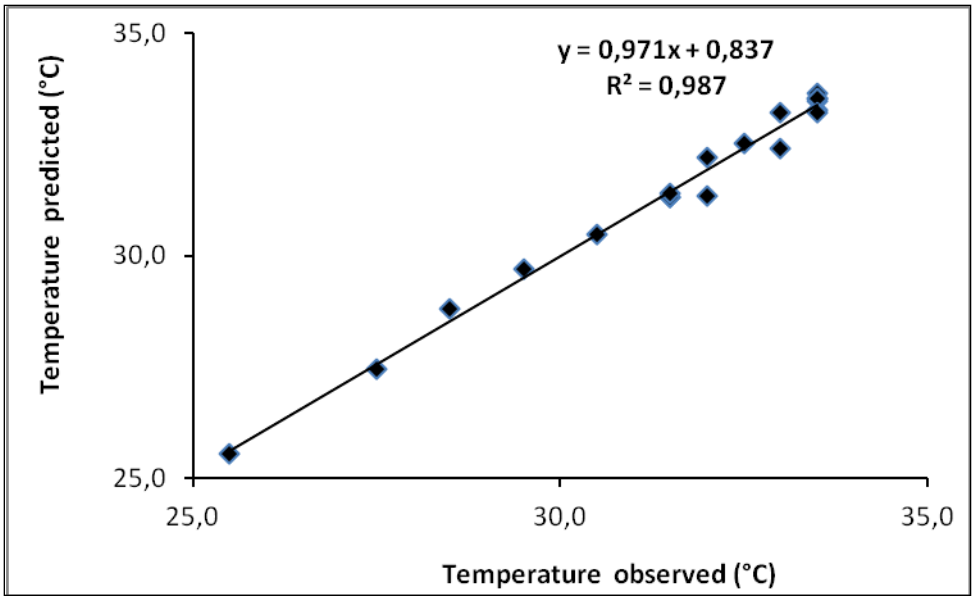


Figure 9: Regression curve between predicted and observed values for temperature

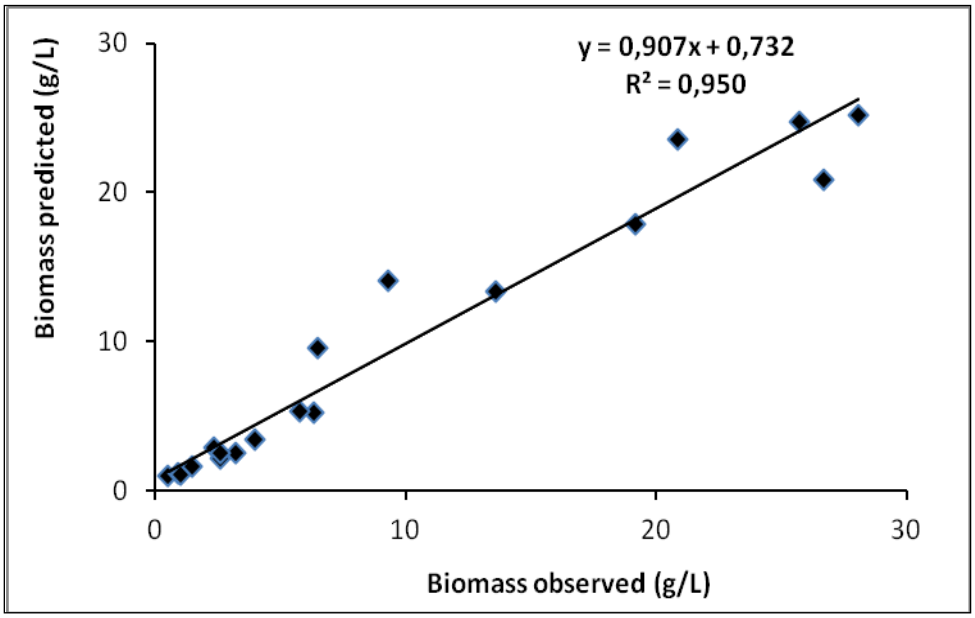


Figure 10: Regression curve between predicted and observed values for biomass

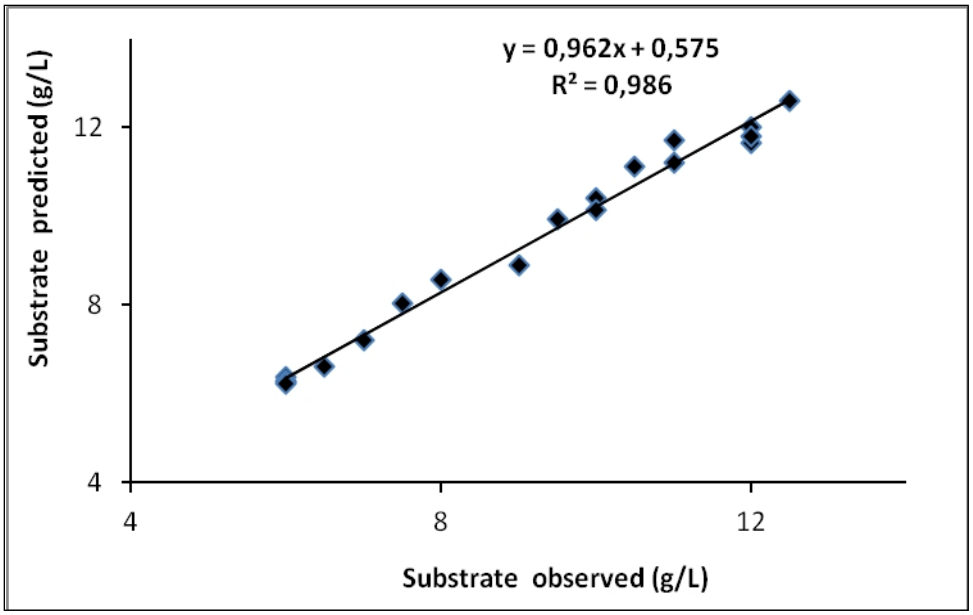


Figure 11: Figure 8: regression curve between predicted and observed values for substrate

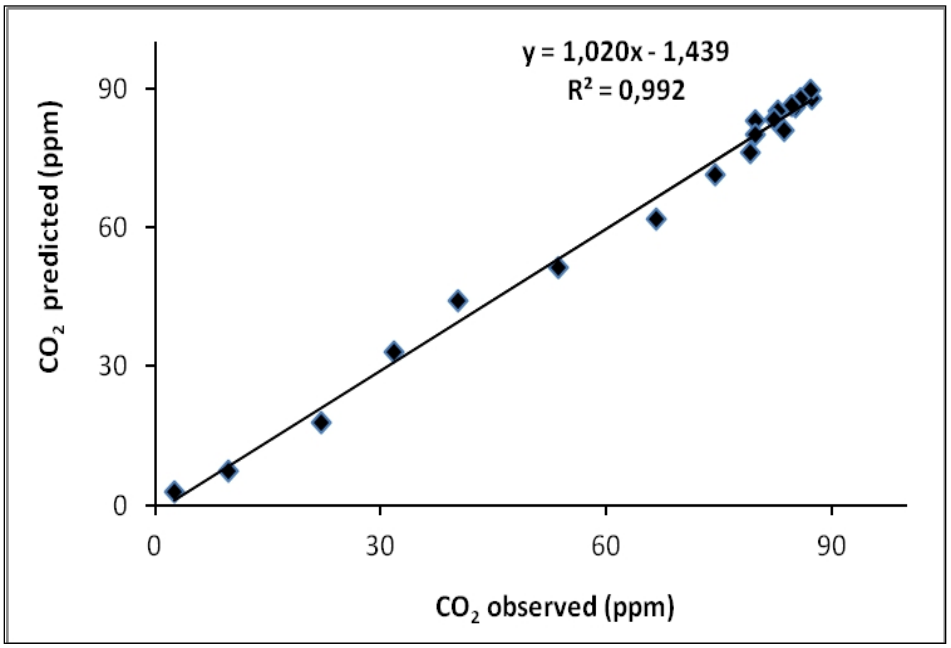
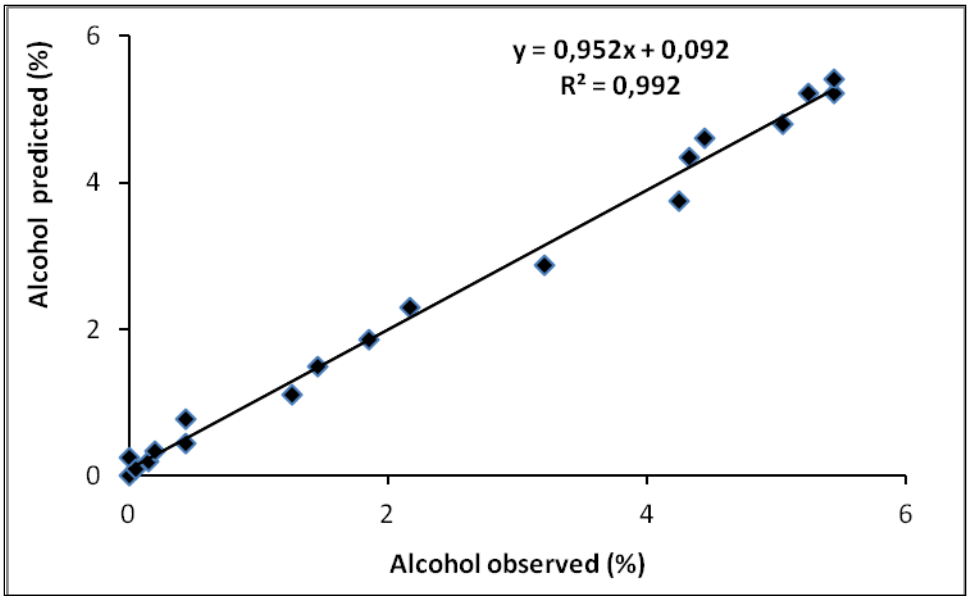


Figure 12: Regression curve between predicted and observed values for CO_2



Figures 13: Regression curve between predicted and observed values for alcohol

Discussion

The prediction capability of artificial neural network depends on its topology. In this work, a multi layer perceptron was used. It is composed by three kinds of layers:

- One input layer (6 neurons);
- One output layer (6 neurons);
- One or two hidden layers whose neurons number must be determined.

If it is easier to find out the number of neurons in the input and output layers, it is not the case for hidden layer (Assidjo et *al*., 2006). However, an appropriate topology may be found by performing network pruning or network growing (Kadhir et *al*., 2000). Starting with a sufficiently big topology, the neural network is pruned by eliminating the links containing insignificant weights using a weight elimination method, e.g., the optimal brain damage (obd) method developed by Le Cun et *al.* (1990). Alternatively, starting with a small architecture, the network is grown until reaching a size, which gives a good prediction model. This last methodology was used in the present study varying neurons from 1 to 10 firstly and increasing the number of hidden layer from 1 to 2. During this step, the neural model obtained is simulated to find out the calculated values of the physicochemical and microbiological parameters. These calculated values are compared with experimental values. The regression line obtained from this comparison is characterized by its correlation coefficients (r). For this purpose, the topology 6-6-6, whose correlation coefficients were all close to

1 while considering the training and validation phases, seems to be the best. Indeed, the best artificial neural network is a compromise between the correlation coefficients obtained during training and those obtained during validation phases (Chaoui *et al*., 2000; Chevret, 2007). Thus, the network which can be retained, taking account all responses to predict fermentation parameters assessed, is 6-6-6 (i.e., 6 neurons in the input layer, 6 neurons in the hidden layer and 6 neurons in the output layer).

Moreover, the ability of networks with two hidden layers was checked. The aim is to check another network with a second hidden layer, which presents a better performance than a single hidden layer (6-6-6). The best neural architecture that leads to a good neural prediction model can be determined by the mean square error (mse) which is the discrepancy between predicted and observed values. For this purpose, the stable evolution of the mean square error (mse) around the limit values whatever the number of neurons in hidden layer seems to reveal that the different neural architectures assessed have the same behavior. Indeed, the curves seem confounded. It is therefore necessary to check out if there are equal or not. To answer this question, analysis of variance method is needed. Anova test was done considering values from 5 to 10 neurons in hidden layer. The results showed that there was a significant difference ($p<0.05$) between behavior of the architectures. A post-hoc test (fisher least significant difference lsd) revealed that the behavior of neural architecture 6-3-x-6 differed significantly from the other ones and presented the relatively highest mse values. For these reason, it does not give interesting results. Moreover, the neural architecture 6-x-6 presents the mse values relatively higher than those of the neural architectures 6-6-x-6 and 6-9-x-6. Thus, the neural architectures with two hidden layers (6-6-x-6 and 6-9-x-6) present a better performance than a single hidden layer (6-x-6). Taking into account mse values, it is very difficult to determine the most efficient neural architecture between 6-6-x-6 and 6-9-x-6. It is therefore necessary to examine the coefficient correlations (r) in addition to mse. It is well known that more higher is r value, more adequate is the network (Assidjo *et al*., 2009).

The analysis of correlation coefficients (r) of the fermentation parameters for a second hidden layer during the training and validation showed clearly that the neural architecture 6-6-10-6 was the best. This network obtained (6-6-10-6) is used to predict the values of the physicochemical and microbiological parameters. This step is performed with the data not used during training and validation phases. The global analysis of prediction depicted points out the good ability of artificial neural network for prediction. Indeed, all parameters evolution (i.e. Ph, temperature, substrate, carbon dioxide, biomass and alcohol) are reasonably well predicted. The artificial neural network models obtained give values

close to the observed ones, whatever the physicochemical and microbiological parameters. In addition, the high determination coefficients (r^2) recorded between the observed values and those predicted by the artificial neuron network topology 6-6-10-6, indicate a good accuracy of prediction. Indeed, according to Thompson *et al*. (1979) and feinberg (1996), more higher is determination coefficient (r^2) value, more adequate is the ability of the network model to properly explain the phenomena. Therefore, the values predicted by the artificial neuron network topology 6-6-10-6 are enough reliable to approximate the batch fermentation process of the sorghum wort. It is a clear indication that the models permit a quite good control of the fermentation process. These results are in agreement with those of Assidjo *et al*. (2006) in the case of modeling the process of brewing beer on industrial scale by the artificial neuron network topology 4-4-4. In addition, Pramanik *et al*. (2004) have successfully used the artificial neural network for predicting of cell mass and ethanol concentration in batch fermentation using *saccharomyces cerevisiae* yeast. This confirms once again the ability of artificial neural networks to approximate the dynamic processes such as fermentations. Thus, it clearly appears that the neural network used in this study is very suitable to simulate the batch fermentation studied.

Conclusion

The artificial neural network, precisely the multi layer perceptron used in this present study has shown its ability to predict the evolution of wort ph, temperature, substrate, carbon dioxide rate, biomass (micro-organisms quantity) and alcohol during time. The high determination coefficients (r^2) between simulated values and observed ones indicate the suitability of artificial neural network for modeling dynamic phenomena. A properly designed artificial neural network for the retained architecture (6-6-10-6) has shown its ability to simulate accurately the batch fermentation studied. It can therefore, be used for controlling the *tchapalo* production at industrial scale.

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