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RESEARCH ARTICLE

MODELING BY ARTIFICIAL NEURON NETWORKS (ANN) OF DRYING (under hot air) OF CASHEW APPLE (*ANACARDIUM OCCIDENTAL* L.)

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ABSTRACT

The cashew apple is a product of proven nutritional importance and perishable due to its high water content. A reduction of this would allow its conservation and can be done by osmosis-drying in order to limit the loss of nutrients. This drying study aimed to describe the behavior of water outflow in cashew apples treated with molasses and sucrose solutions in order to predict their final water content. Drying experiments were carried out on fresh cashew slices in an oven at 50°C by static gravimetric weighing. The drying data was used to create and simulate the evolution of the water content from an artificial neural network (multilayer perceptron). The results indicate that the 4-2-1 structure artificial neural network exhibited the best abilities to predict and simulate the end-of-drying water content of cashew apples treated with $R^2 > 0.9999$ and EQM (9.7252 E -09) $<10^{-9}$.

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INTRODUCTION

The economy of Côte d'Ivoire is strongly based on its agricultural development which represents 19.9% of its GDP (World Bank, 2023). This agriculture takes into account export crops, such as coffee, cocoa, and diversification crops such as mango and cashew (Ouattara, 2018). Côte d'Ivoire is the leading producer with more than 968,676 tonnes (CCI France Côte d'Ivoire, 2022). After harvest, the false fruit, which represents nearly 85% of the weight of the fruit, is valued very little (Kouadio *et al*., 2022). This leads to losses of around 6 million tonnes (CCI France Côte d'Ivoire, 2022). This huge post-harvest loss is attributed to several factors including insufficient proper post-harvest knowledge and skills as well as perishable properties of cashew apple (Nwosu *et al*., 2016). However, the cashew apple is subject to rapid rotting upon harvest due to its high water content (about 85%) which promotes the proliferation of spoilage germs. In order to improve the shelf life, different drying methods have been developed (Abouo *et al*., 2015a). Drying reduces the water activity in a food (Abouo *et al*., 2021). It can be carried out with, before or after different types of treatment that also help to reduce the initial water content of the fruit or to modify the structure of the fruit tissues so as to accelerate drying (Fernandez *et al*., 2008). Solution pretreatments are water removal processes in which cellular materials, such as fruits and vegetables, are immersed in a concentrated solution of sugar or salt.

The work of Azoubel and Murr (2003) significantly improved the drying process to achieve maximum water loss and minimum solids permeation using sucrose and corn syrup. Drying makes it possible to reduce the water content, for these reasons, it is necessary to control it in order to optimize it (Abouo *et al*., 2020). Control of drying necessarily implies an ability to predict, at any time, the evolution of the physical characteristics of drying such as the water content of the product (Abouo *et al*., 2020). This ability can be achieved through modeling (Nogbou *et al*., 2015). Several mathematical models have been proposed to describe the drying process. They can be classified into theoretical models, semi-empirical models and empirical models (Prati, 1990). The theoretical models, depending on their complexity, finely detail the transfer mechanisms. Unfortunately, the difficulty of obtaining certain parameters sometimes limits their use. Semi-empirical and empirical models do not make it possible to distinguish all the internal mechanisms of water transfer. However, because of their ability to make good adjustments, they are widely used in drying works, particularly in the description of the behavior of water in the product (Dadali *et al*., 2007; Hii *et al*., 2008, Murthy and Manohar, 2012). Among these models, artificial neural networks have been of particular interest in the field of drying for several years. Indeed, several researchers have used artificial neural networks as a modeling tool to predict the physical parameters of drying (Ramesh *et al*., 1995; Sreekanth *et al*., 1998; Hernandez-perez *et al*., 2004; Nogbou *et al*., 2015).

Faced with the numerous post-harvest losses recorded, the very small amount of scientific data on this subject and the scientific progress made from the drying of various agricultural matrices, it seems appropriate to carry out investigations which will contribute to providing solutions to the problem of post-harvest losses of cashew apples by modelling. This work consists of:

- Characterize the drying of cashew apples through the establishment of drying curves;
- Model and simulate the drying process of sliced cashew apples using an artificial neural network;

MATERIAL AND METHODS

Sample preparation: The biological material consists of twenty-five (25) kilograms of cashew apples harvested from plantations in the city of Yamoussoukro (economic capital of Côte d'Ivoire) in February 2023 (Figure 1). The samples were transported to the laboratory for further work. The false fruit was separated from the nut, and the apples were soaked in the solutions of (molasses, sucrose) according to the experimental domain of the central composite plan (Table 1).

Figure 1. Harvested cashew apple sample

Table 1. Experimental domain of the composite central plan

Valeurs codées / réelles					
Parameters	-r	-1	0	1	+r
X_1 (Soaking)	3	6.074	13.5	20.93	24
X_2 (Concentration °B)	50	52.93	60	67.07	70

Cashew Apple Drying Procedure: The soaked cashew apples were subsequently cut into slices and dried in an oven (MMM MEDCENTER Venticell, Berlin) at fifty (50°C) degrees. The drying tests were carried out and the differential loss of mass of the samples was noted by static gravimetric weighing using a balance (Sartoruis, A200S, France) until the difference between three (03) weighings successive (every hour) does not exceed the value of 0.001 (Belhamidi *et al*., 1999). At the end of drying, the residual water content was determined according to the AOAC method (2005). Table 2 presents the information relating to the experimental tests carried out. The equilibrium water contents of the dried samples (dry cashew apple slices) were determined from the following equations:

$$X^* = \frac{X_t - X_e}{X_0 - X_e} \quad (1)$$

$$\frac{dX}{dt} = \frac{X_{t+dt} - X_t}{d_t} \quad (2)$$

With: Xt: water content at instant t / Xe: equilibrium water content / X0: initial water content

Table 2. Composite center plan experiment board

Test N°	Variables	
	X_1 (Soak time (H))	**X_2** (Solution concentration (°B))
1	6.074	52.93
2	6.074	67.07
3	20.93	52.93
4	20.93	67.07
5	3	60
6	24	60
7	13.5	50
8	13.5	70
9	13.5	60
10	13.5	60
11	13.5	60
12	13.5	60
13	13.5	60

°Brix (soluble solids matter)

Architecture of the artificial neural network: The neural network used in this study is a multilayer perceptron. It consists of layers: input, hidden and output. The input layer neurons represented the input variables which were respectively the soaking time (X_1), the concentration of the molasses or sucrose solution (X_2), the initial water content of the slices (X_3) and the drying time of the cashew apple slices (X_4). The output layer neuron represented the output variable which was the final water content of the cashew apples (Y). The activation function on the hidden layer was the hyperbolic tangent function (Tanh) (Assidjo *et al*., 2006). The linear function was used as an activation function on the output layer. A normalization, in an interval of [-1; 1], was first performed on all the experimental data. The learning phase was supervised using the Levenberg-Marquardt algorithm. According to the composite matrix, thirteen (13) tests were carried out for each type of solution (02) used and one (01) for the control sample. That is twenty-seven (27) attempts repeated ten (10) times. Fifty percent (50%) of this experimental data base was used to constitute the learning base of the ANN. For validation, twenty-five (25%) of experimental data was employed. Finally, to assess the quality of generalization of the ANN, 25% of the experimental data having served neither for the learning process nor for the validation, was used. Initially, 1 neuron was used on the hidden layer. The network was built using Matlab R2016a software (MathWorks Inc., Massachusetts, USA).

Optimization and simulation of the neural network: To obtain the best neuronal structure, the number of neurons on the hidden layer was optimized. This optimization consisted in varying from 1 to 10, the number of neurons on the hidden layer. There is no rule for choosing the number of neurons in the hidden layer Laïdi and Hanini (2012). For each neuronal structure, the calculations were repeated 1000 times. Then, the coefficient of determination (R^2) and the root mean square error (RMSE) of each structure were determined. The best ANN was the one that had the highest R^2, the lowest RMSE with an uncomplicated topology. Once selected, the best ANN was used to simulate randomly chosen trials. The quality of the simulation was assessed using the R^2 and the mean absolute error (MAE) (Nogbou *et al*., 2015).

Statistical analyzes: A computer calculation program based on the method of artificial neural networks (ANN) of the multilayer perceptron type was developed and implemented in the MatLab R2016a software for the calculations followed by the determination of the optimal neuronal structure (Nogbou *et al.*, 2015).

RESULTS AND DISCUSSION

RESULTS

Drying curve and speeds: An average adjustment from point clouds was used to establish drying curves and calculate average drying rates. The evolution of the differential mass loss of the samples during drying is illustrated in figure 2. The mass loss presents a general decreasing trend. Three (03) drying phases emerge. The first (01) qualified as temperature setting is observed during the first two (02) hours of drying for all the samples. The second phase is observed from the 2nd hour of drying to the 18th hour. This is the constant speed drying phase. The slowing phase just after the end of the second phase and this until the end of drying occurring around the 34 cumulative hour of drying. The average drying rates determined are expressed in g H_2O/g.MS/h and are as follows:

- 0.1429 for the control sample (untreated: ET)
- 0.0921 for samples from treatment with sucrose (E. sac)
- 0.0972 for samples from treatment with molasses (E. mel)

Modeling of the Artificial Neural Network (ANN): Table 3 presents the performance of the best neuronal structures for each hidden neuron. Analysis of this table shows that the coefficient of determination (R^2), during the learning phase, varies between 0.97768 and 0.99999.

Overall, this indicates a very good correlation between the values calculated by the neural structures and the experimental values of the learning base. Moreover, the root mean square error (RMSE) analysis confirms this observation.

Indeed, the RMSE fluctuates between 0.8254 E-03 and 9.7252 E-09. These values close to 0, attest to the good convergence observed between the calculated values and the experimental values.

Overall, the performance criteria of the neural structures are substantially close. However, the 4-2-1 neuronal structure (4 neurons on the input layer, 2 neurons on the hidden layer and 1 neuron on the output layer), present during the learning, testing and validation phase (Table 3), the highest R^2 (0.99999) and the lowest MSE (9.7252 E-09). It is the most appropriate neuronal model. The values of the weights and the biases of this neuronal structure are presented in tables 4 and 5.

Neural network simulation: Figure 4 presents simulations of the drying of treated and untreated cashew apples. The analysis of this figure shows a very good match between the experimental values and the simulated values.

This results in the high values of R^2 ($0.9999<R^2<0.9999$), illustrated by Table 3. In addition, the analysis of the mean absolute errors ($0.0222 < MAE < 0.0294$), confirms the quality of the adjustment of the ANN (Figure 5). The random distribution of the residuals indicates that the ANN also has a very good ability to make predictions.

Table 3. ANN performance criteria for learning, testing and validation

Hidden Layer Neuron Number	R^2 Learning	R^2 Test	R^2 Validation	RMSE
01	0.97768	0.98194	0.96717	0.8254 E-03
02	0.99999	0.99999	0.99999	9.7252 E-09
03	0.99999	0.99946	0.99993	2.7677 E-06
04	0.98436	0.97608	0.98365	8.2333 E-03
05	0.99999	0.99936	0.99982	6.9981 E-06
06	0.99991	0.98247	0.99465	5.2399 E-03
07	0.99994	0.97636	0.98832	5.9587 E-03
08	0.99999	0.97510	0.98544	1.3821 E-03
09	0.99999	0.97517	0.97451	2.6601 E-03
10	0.99999	0.97315	0.98526	3.6547 E-03

Table 4. Values of weights and biases on the hidden layer of the ANN (4-2-1)

Hidden layer neuron	X_1	X_2	X_3	X_4	Error (*bi*)
N1	1.8847	0.3901	-3.6097	-0.1780	-3.4405
N2	0.0001	0.0000	-0.1222	-0.0000	-0.0237

Table 5. Values of the weights and biases of the ANN output layer (4-2-1)

Neuron layer Release	Weight		General error (B)
	N_1	N_2	
Y	0.0040	-8.2244	-0.1920

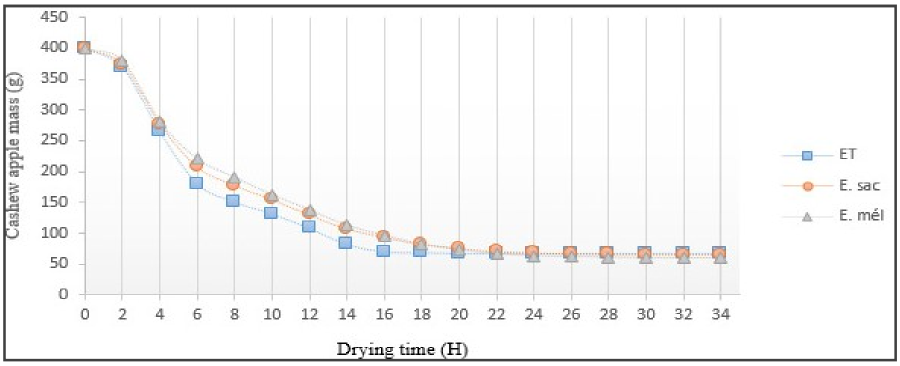

Figure 2. Evolution of the differential loss of mass of apple slices during drying

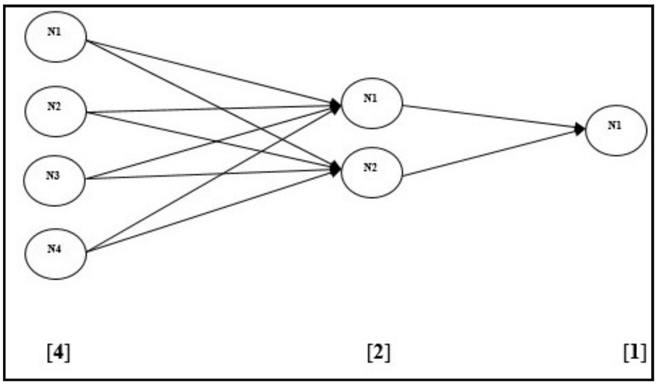

Figure 3. Retained Multilayer Perceptron (ANN 4-2-1)

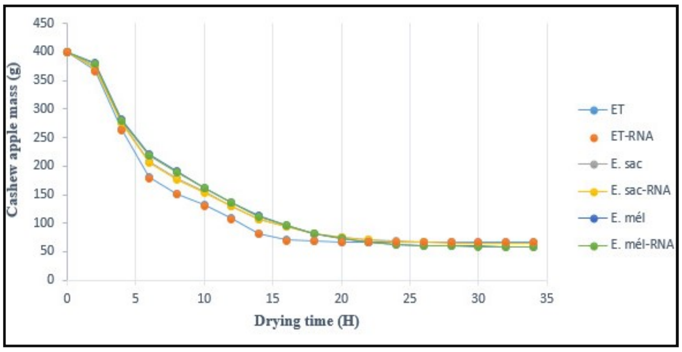

Figure 4. Evolution of the differential loss of mass of apple slices during drying (experimental and predicted by ANN 4-2-1)

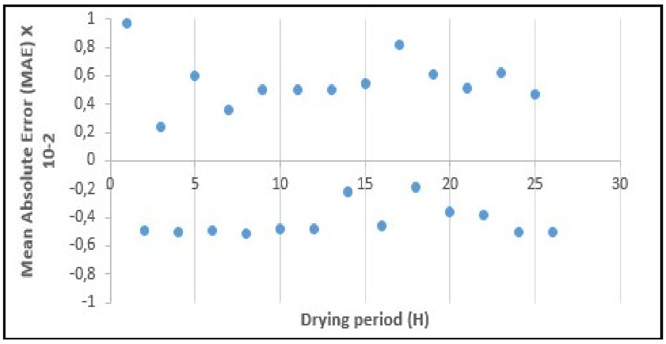

Figure 5. MAE fluctuation during the simulation

DISCUSSION

The resulting differential moisture content loss drying curve is similar to that of other agricultural products obtained in several hot air drying studies (Abouo *et al.*, 2020). It presents a decreasing exponential pace and indicates that it is a function of the time/temperature couple as indicated by the work of Chekroune (2009) during the drying of dates. The modeling of cashew apple drying by an artificial neural network is done in two steps. The first step was to determine the best neural structure capable of correctly fitting the experimental data. The second step was to use the chosen ANN as a prediction tool (Nogbou *et al.*, 2015). Regarding the first step, adjusting the number of neurons on the hidden layer is used as a technique for optimizing the neuronal structure. This technique has been used in some works (Özkaya *et al.*, 2008; N'goran *et al.*, 2009; Kouamé *et al.*, 2013). It made it possible to obtain 10 neuronal structures.

These structures were analyzed using R^2 and RMSE. The analysis of these performance criteria made it possible to retain the 4-2-1 neuronal structure. This structure presents after the test and validation learning phases, the highest R^2 and the lowest RMSE. These results suggested that the ANN retained has a good capacity for generalization, that is to say a good capacity to give a satisfactory response to an input which is not part of the data of the learning phase. These results are close to those obtained by N'goran *et al.* (2009), in the case of modeling the osmotic dehydration of mango (*Mangifera Indica* L.), Nogbou *et al.* (2015) in the case of modeling the intermittent drying of cocoa beans (*Theobroma cacao* L.). The results obtained following the simulation of the ANN (4-2-1), highlighted high R^2 and low RMSE. Indeed, the R^2 were respectively 0.9999, 0.9999 and 0.9999 for the three sets (learning, testing and validation). The relative MAE moved from 0.00183-0.00965. These results revealed a good match between the predicted values and the experimental values. They confirm the good ability of ANN (4-2-1) to predict the behavior of cashew apples during hot air drying. These results are close to those reported in some studies. Kouame *et al.* (2013), for example, in the case of plantain growth modeling, obtained an optimal neuronal structure (7-2-7), with R^2 greater than 0.97. Other authors like Assidjo *et al.* (2006) successfully used an ANN ($R^2 > 0.95$) to model alcoholic fermentation in breweries. It was the same for Murty and Manohar (2012), Erenturk and Erenturk (2007) and Goni *et al.* (2008).

CONCLUSION

The objective of this study was to model the kinetics of water during drying of cashew slices at 50°C. The drying kinetics were found to have a decreasing exponential rate. The artificial neural network (multilayer perceptron) of structure 4-2-1 presented a coefficient of determination of the subsets (learning, test and validation) close to 1 (R^2=0.9999) and a low mean absolute error (MAE). This demonstrates a good ability to predict the moisture content during drying of cashew apples in sliced form.

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