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Modelling of Osmotic Dehydration of Mango (*Mangifera Indica*) by Recurrent Artificial Neural Network and Experimental Design

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Abstract: Osmotic dehydration process was investigated in this paper. Mango slices samples were osmotically dehydrated in different hypertonic solutions of glucose and sucrose at three different temperatures (30, 50 and 60°C) without agitation. A full factorial design, used for experiments, was shown significant effect of sugar concentration on water loss. But no significant effect was observed for sugar type or temperature on this response (water loss), due certainly to small thickness (1 mm) of samples. The modelling of the process with recurrent artficial neural network proves the ability of this method for osmotic dehydration process modelling with good accuracy (R > 0.967).

Key words: Osmotic dehydration, recurrent artificial neural network, mango, water loss, full factorial design

INTRODUCTION

Water elimination is a suitable way to protect foods from spoilage. Indeed, the lack of water prevents foods from the microorganisms development. In these conditions, few enzymatic activity is possible and the major part of chemical reactions are slowed down[1]. In order to better protection, practically all water quantity in foods must be carried away. But, it is sometimes avantageous to reduce water quantity (minimizing the energy cost) before drying foods. In this perspective, osmotic dehydration is one of the methods that can pretreat foods without products structure damages[2, 3]. Osmotic dehydration is a partial dehydration method applied to fruits and legumes. It consists in immerging the entire or piece of products in highly concentrated solutions[1, 4]. During this process, two simultanous phenomena occur[4]:

- Important leave of water from food to solution. Water diffusion is due to concentration gradient between the food and the solution through food cellular membrane;
- Solute transfer from solution to food. Indeed, due to the structure complexity of cellular membrane, it acts as semi-permeable membrane. And as its compartiments are partially selective, some solutes diffuse towards foods.

Moreover, water diffusion is concommittent to some natural substances (e.g. vitamins, acids, minerals, saccharides, colorants...) one[2]. But this flow can quantitatively be negligected. Osmotic dehydration, as pretreatment technique to different conservation and transformation methods, preserves and improves food organoleptic, sensorial and nutritional properties. It efficient even at ambient temperature. Thus damage caused by heating is reduced to minimum and energy consumption is utmost null.

Osmotic dehydration of foods has gained attention recently due to its potential for the food process industry[1, 4-6]. Generally, it will not give a product of sufficiently low moisture content to be considered shelf-stable. Consequently, osmosed product should be further processed (generally by air, freeze or vacuum drying) to obtain a shelf-stable product or used as a pretreatment for canning or freezing.

The osmotic agents are sugars (e.g. sucrose, glucose, sorbitol) and salts according to expected final product quality[6-8]. However, different solutes can be combined[8-10].

The influence of factors like concentration, osmotic solution composition, temperature, immersion time, agitation nature and shape of fruit or legume on mass transfer and food quality was extensively studied on different foods such as carott[11], pineapple[12], melon[13], apple[14].

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Lima *et al.*[15] have shown that when concentration and temperature of osmotic solution increase, mass transfer rate increases too till an equilibrium point. Beyond this point, indesired flavour, texture and colour of food were observed.

In order to develop an efficient technology of food treatment based on osmotic dehydration, it is necessary to monitor the phenomenon to set the desired dehydration and impregnation levels.

The modelling of mass transfer during osmotic dehydration was performed using analytical and empirical models based on the Fick second law[4, 16]. These models are complex and specifc to some treatment conditions above all food geometric configuration. Moreover, they depend on empirical constants that must be known prior used.

The purpose of this paper is to use an artifcial neural network to modelling the mass transfer kinetics of mango (*Mangifera indica*), a fruit that contains about 82 per cent of water[17].

MATERIAL AND METHODS

Vegetal Material: Mango samples, bought in local market, after washing, were cut in slices of about 1 mm thick, 3 cm large and 7 cm long. Hypertonic solutions were prepared and put in containers with samples. The set was put in a shaker. The samples solution ratio was 1:10 to avoid solution dilution.

During the osmotic dehydration, at each hour, samples were removed, washed and dried with absorbent paper before being weighted.

Experimental Design: The experimental design is a statistical tool which purpose is to point out relationships that can exist between a dependent variable (response) and factors (parameters)[18]. It consists in studying these relationships by varying together all factors under study, and to appreciate the effect of these variations on the response. The design of experiment used herein is a Full Factorial Design (FFD). This design enables the estimation of a polynomial model defined as following:

$$y = a_0 + \sum a_i X_i + \sum\sum a_{ij} X_i X_j + \sum\sum\sum a_{ijk} X_i X_j X_k \cdots \tag{1}$$

The experimental design was evaluated using coded levels -1 to +1 according to levels number. The independent variables were sugar type, concentration and temperature and the dependent one (response) being Water Loss (WL) (Table 1).

Artificial Neural Network: The multilayer Perceptron (MLP) organization of the units is the most used neural network architecture for the applications in engineering[19-21]. It consists of computational units organized into three kinds of layers: input, hidden, and output layer (figure 1).

In order that an MLP network approximates the nonlinear relationship existing between the process inputs and the outputs, it needs to be trained in a manner such that a pre-specified error function is minimized. In concrete terms, the MLP-training procedure aims at obtaining an optimal set (W) of the network weight matrices W_H and W_O, that minimize an error function. The commonly employed error function is the *root-mean-squared error* (RMSE) defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N_p} E_i}{N_p K}} \tag{2}$$

where N_P refers to the number of patterns used in the training; i denotes the index of the input pattern (vector); and E_i represents the *sum-squared error* (SSE) pertaining to the i_{th} training pattern. The SSE is expressed as:

$$E_i = \sum_k^K (t_k^i - y_k^i) \tag{3}$$

where t_k^i and y_k^i are the desired (target) and predicted values of the k_{th} output node, respectively. The most widely used formalism for the RMSE minimization is the *error-back-propagation* (EBP) algorithm based on a gradient-descent technique known as the *generalized delta rule* (GDR)[22]. In the EBP methodology, the weight matrix set, W, is initially randomized. Thereafter, an input vector from the training set is applied to the network's input nodes and the outputs of the hidden and output nodes are computed. The outputs are computed as follows. First, the weighted sum of all of the nodes specific inputs is evaluated, which is then transformed using a nonlinear activation function, such as the sigmoid (i.e. tanh). The outputs from the output nodes (y_k^i) are then compared with their target values (t_k^i), and the difference is used to compute the SSE defined by equation 3. Upon SSE computation, the weight matrices W_H and W_O are updated using the GDR framework.

MLP are then supervised techniques, operating an implicit mapping from an input X space output Y space, based on a set of input/output pairs.

During the last decade, application of artificial neural network in identification and control has been

Table 1: The coded and real values of the studied independent variables

Variable	-1	0	1
Sugar	Glucose	xxxxx	Sucrose
Concentration (%)	50	60	70
Temperature (°C)	30	45	60

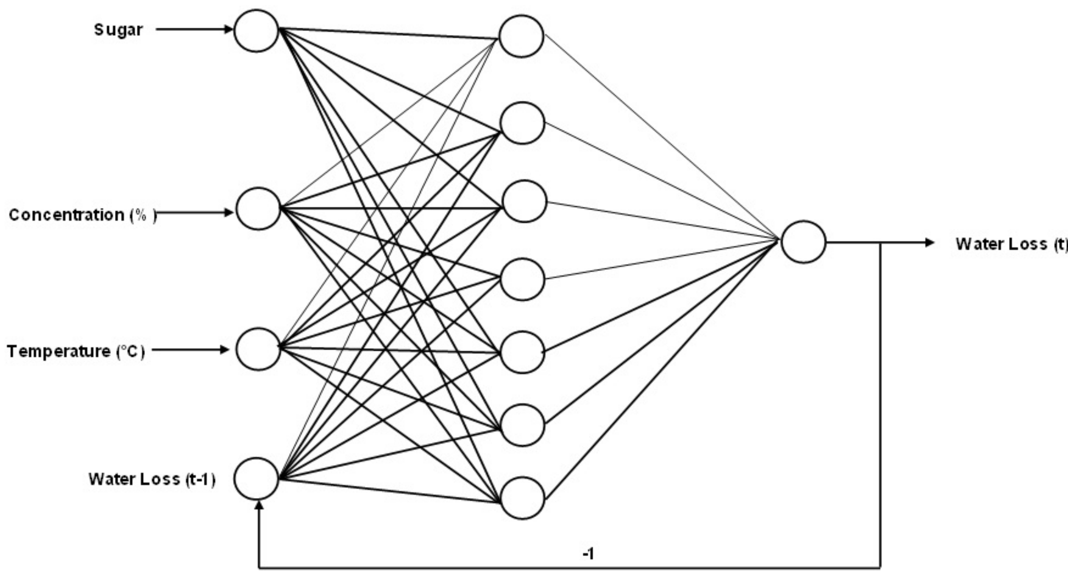

Fig. 1: A recurrent artificial neural network architecture

increased exponentially[23, 24]. The wide spread of application has been due to the following attractive features:

- artificial neural networks present good ability to approximate arbitrary nonlinear functions;
- they can be trained easily by using past data records from the system under study;
- they are readily applicable to multivariable systems;
- they do not require specification of structural relationship between input and output data.

RESULT AND DISCUSSION

Effects of Variables on Response: The osmotic process was studied in terms of water loss. Results obtained are plotted in figure 2. An initial high rate of water removal followed by slower removal in the later stages was observed. Rapid loss of water at the beginning is apparently due to the large osmotic driving force between the dilute sap of the fresh fruit and the surrounding hypertonic medium. Several research groups have published similar curves for osmotic dehydration of foods[4, 6, 7].

Increase in solution concentration led to an increase in the osmotic pressure gradients and, therefore, higher water loss values throughout the osmosis period were obtained (figure 2A).

The results indicate that a higher medium concentration lead to a faster water loss. In addition, sucrose allows the formation of a sugar surface layer, which becomes a barrier to the removal of water and the solute uptake. The water loss was lower using glucose than sucrose (figure 2B), as already published[10, 25, 26]. Indeed, the former increases the driving force for dehydration owing to its water activity lowering capacity and its low molecular weight allows a higher rate of penetration in the material. Its use is therefore quite limited since a sweetened taste is imparted to the food.

In figure 2C, it is observed that higher is the temperature, higher are the water loss values. Moreover, it appears that even at ambient temperature (i.e. 30°C), samples dehydration occurs confirming many previous published results[4, 6, 7, 15].

From the results given in table 2, the coefficients of the polynomial model (1) were determined using a classical multiple linear regression method.

The different coefficients obtained are presented in table 3. It can be noted that the coefficients range from -3.251 (a_{23}) to 47.089 (a_0). The associated probability (p) varies from 0.0000 to 0.8237. This represents the probability to mistake taken the corresponding coefficient as significantly different to 0. Therefore, we choose $p \leq 0.05$ as the relevant probability, the different significant coefficients (in bold in the table 3)

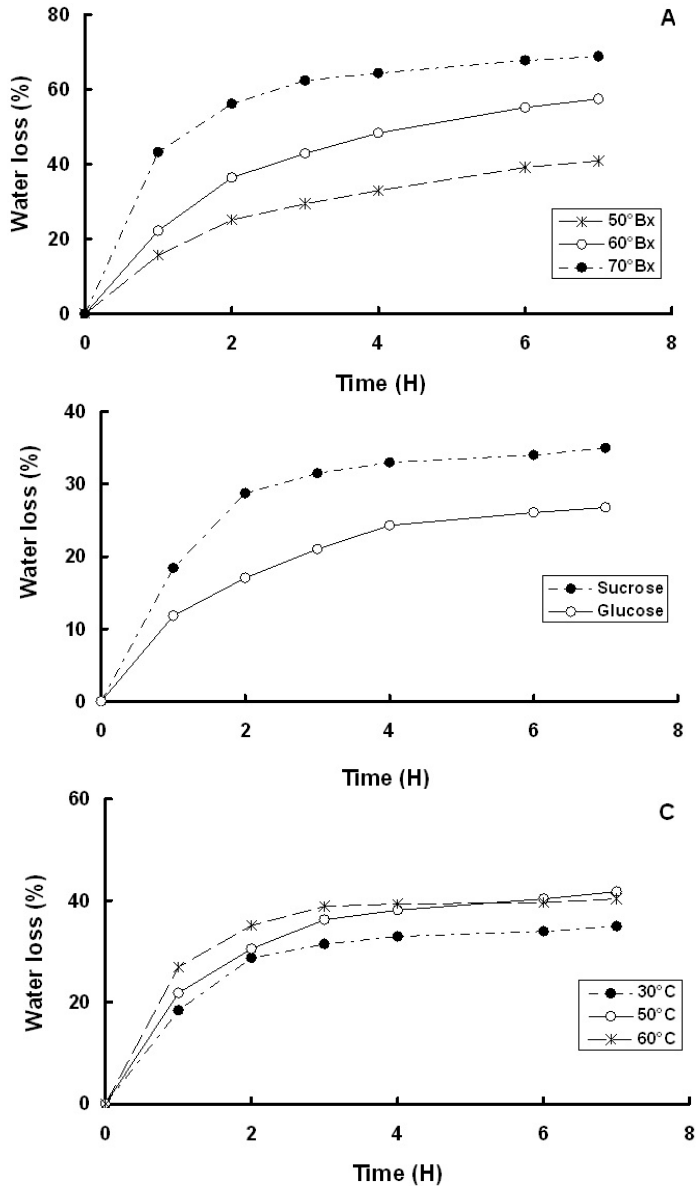

Fig. 2: Effect of sugar concentration and type (upper) and temperature (lower) in the osmotic dehydration (A: Glucose, 45°C ; B: 45°C, 50°Bx; C: Saccharose, 50°Bx)

are the average and the concentration ones. Otherwise, this results point out that sugar type and temperature have no significant effect on mango osmotic deshydration process.

The concentration effect on osmotic dehydration process was already revealed by many authors[27, 28]. Fernandes *et al.*[28], for instance, have shown that the increase of osmotic solution concentration increases the fruit water loss. They also point out that the effect of solution concentration on mass transfert coefficient is higher than the temperature one. The same result has been obtained by Andrade *et al.*[27], who have also found that immersion time has no significant effect on the water diffusion coefficient.

The non significant effect of sugar type seems unexpected. But the different results published show that this effect is more relevant. Indeed, when sugar molecule is small (e.g. sorbitol, glucose), the solute trends to penetrate the fruit inceasing the solid gain and reducing the water loss, contrary to bigger molecule like sucrose[27, 29, 30]. The non relevant effect of sugar type and temperature can be due to the weak thickness of mango samples (1 mm) used during the study, taking in account diffusion coefficients, found in litteratues for different foods, that are in the range 0.5-2×10^{-10} m²/s[7, 25].

Table 2: Experimental design and water loss values obtained after 7 hours immersion

Run	Sugar	Concentration (%)	Temperature (°C)	Water loss (%)
1	Sucrose	50	30	34.982
2	Glucose	50	30	26.723
3	Sucrose	60	30	48.011
4	Glucose	60	30	46.628
5	Sucrose	70	30	53.085
6	Glucose	70	30	46.628
7	Sucrose	50	45	41.75
8	Glucose	50	45	40.87
9	Sucrose	60	45	57.419
10	Glucose	60	45	52.519
11	Sucrose	70	45	68.795
12	Glucose	70	45	63.842
13	Sucrose	50	60	43.556
14	Glucose	50	60	40.339
15	Sucrose	60	60	48.38
16	Glucose	60	60	38.189
17	Sucrose	70	60	55.42
18	Glucose	70	60	40.474

Table 3: Effects of independent variables

	Effect	Probability
Global average	**47.089**	**0**
(1) Sugar	2.516	0.2395
(2) Concentration	**8.335**	**0.007**
(3) Temperature	0.859	0.7347
1x2	0.341	0.8926
1x3	1.021	0.6872
2x3	-3.251	0.3065
1x2x3	1.691	0.5874

Modelling: In order to monitor the osmotic dehydration process using a black box model, an artificial neural network, with the classical back propagation algorithm, was used. Data set was divided in two subsets: 75 % data for training subset and 25 % for test one.

To find out the best network for the modelling of osmotic dehydration process, hidden neurons number was varied from 1 to 10. The performance values concerned the MSE (mean square error) and correlation coefficient (R) between observed and calculated values are represented in table 4.

The analysis of this table shows that MSE values range from 0.0007 (training) to 0.0439 (test). The minimal value is achieved when there is 10 neurons in the hidden layer for training and 8 for test subsets. Parallely, R varies from 0.9205 (test) to 0.9996 (training). Highest value is reached for 10 and 7 hidden neurons, respectively for training and test subsets. If it is admitted that a network is optimal when its MSE value is lower, its R one is higher and it possess few

Table 4: ANN model performance criteria

	Training		Test	
	R	MSE	R	MSE
1	0.9439	0.02	0.9261	0.0262
2	0.973	0.0099	0.9191	0.0281
3	0.9862	0.0108	0.9237	0.0231
4	0.993	0.0054	0.9222	0.0252
5	0.9966	0.0072	0.9355	0.0337
6	0.9976	0.0043	0.9337	0.0302
7	**0.9985**	**0.001**	**0.9427**	**0.0228**
8	0.9988	0.0013	0.9205	0.0224
9	0.9991	0.002	0.9355	0.0439
10	0.9996	0.0007	0.9214	0.0309

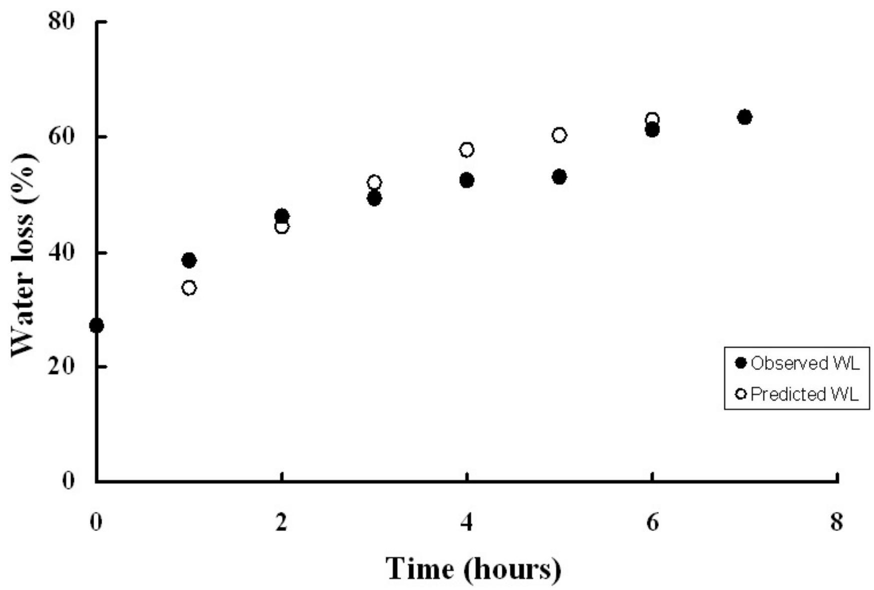

Fig. 3: Comparison of predicted and observed values of water loss

neurons in the network, the best compromise for the recurrent artificial network, taking account both subsets, is the architecture 4-7-1. That to say 4 neurons in input layer, 7 nodes in hidden layer and 1 neuron for output, as depicted in figure 1.

This architecture was used to monitor the mango osmotic dehydration process and compared to data not used during training and validation calculations. Figure 3 presents the results obtained. It appears a very good adequacy between predicted and observed data with correlation coefficient R higher than 0.967. This fact is also confirmed by normal distribution and low values (ranging from -7.22 to 4.78) of residuals (figure 4).

These results point out the ability of recurrent artificial neural network for suitable modelling of the osmotic dehydration process of mango slices.

Conclusion: The rate of water loss in the osmotic dehydration process of mango was found directly related to solution concentration. Nevertheless, no significant effect was observed for temperature (in the range of 30 to 60°C) and sugar type (glucose or sucrose) on water loss phenomenon.

On the other hand, the osmotic dehydration process was modelled using a recurrent artificial neural network. The topology 4-7-1 presented the best fitting for water loss experimental data with R superior to 0.967.

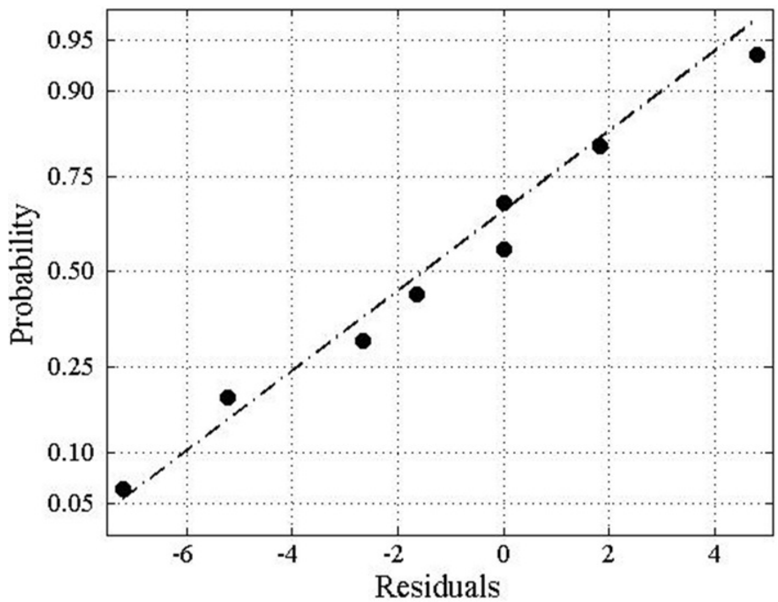

Fig. 4: Normal plot of residuals

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