

## Short communication

## Optimum operating conditions for heat and mass transfer in foodstuffs drying by means of neural network inverse

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## ARTICLE INFO

## Article history:

Received 12 September 2007

Received in revised form 24 June 2008

Accepted 7 July 2008

## Keywords:

Neural network inverse

Heat and mass transfer

Drying

Cassava

Mango

Optimal parameters

## ABSTRACT

Artificial neural network inverse (ANNi) is applied to optimize the operating conditions on heat and mass transfer during foodstuffs drying. This proposed method (ANNi) inverts the artificial neural network (ANN) and uses the Nelder–Mead simplex method of optimization to find the optimum parameter value (or unknown parameter) for given required conditions. In the aim to demonstrate this ANNi method, two separate feedforward networks (ANN) with one hidden layer reported by Hernández-Pérez, García-Alvarado, Trystram, and Heyd [Hernández-Pérez, J. A., García-Alvarado, M. A., Trystram, G., & Heyd, B. (2004). Neural networks for the heat and mass transfer prediction during drying of cassava and mango. *Innovative Food Science and Emerging Technologies*, 5, 56–64], were used in order to obtain temperature and moisture kinetics simulations during the drying of mango and cassava. These reported models take into account air temperature, air velocity, shrinkage as a function of moisture content, time and air humidity as well-known input parameters. Levenberg–Marquardt learning algorithm, hyperbolic tangent sigmoid transfer-function, linear transfer-function and three neurons in the hidden layer were considered in both reported models. Results of the ANNi showed a good agreement with the experimental and simulated data (error < 0.001%). Then ANNi could be applied to determine the optimal parameters during mango and cassava drying with elapsed time minor to 0.3 s. In addition, this methodology can be used to controlling the drying process.

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## 1. Introduction

Air-drying is an essential procedure in food processing industries. Food drying process involves simultaneous heat and mass transfer, which have been modeled with different levels of complexity (Balaban & Piggot, 1988; Karathanos, Villalobos, & Saravacos, 1990; Kiranoudis, Maroulis, & Marinos-Kouris, 1993; Zogzas & Maroulis, 1996; Hernández, Pavon, & García, 2000; Xueqiang & Xiaoguang, 2007). In order to obtain, the optimum operating conditions in the drying process on-line, mathematical description of heat and mass transfer during the drying process is required. There are some works that permit to calculate optimum operating conditions using different mathematical models (Teeboonma, Tiansuwan, & Soponronnarit, 2003; Dutta, Dutta, & Banerjee, 2004; Lee & Pyun, 1993). For example, Elustondo, Mujumdar, and Urbicain (2002) evaluated the optimum operating conditions in drying foodstuff with superheated steam. The authors solved the mass and energy balance equations and converted them into a general initial drying rate equation, where all dryer characteristics were grouped into one dimensionless parameter. Normally, the param-

eters to optimize in the drying process are: inlet air temperature, air flow rate, a shorter total drying time, humidity. However, the calculation of optimal parameters gets sometimes difficult and requires special software, especially when the complexity of the drying process is considered.

Empirical models are used to control on-line, the drying process. For example, artificial neural networks models are developed for a rapid calculation of the drying rates (Islam, Sablani, & Mujumdar, 2003) as well as to predict the temperature and moisture content on-line, during the drying process (Hernández-Pérez, García-Alvarado, Trystram, & Heyd, 2004). Artificial neural networks were inspired in the study of neurosciences (Bishop, 1994). At present, they have a large number of applications in food industry (Boilleux, Cadet, & Le Bail, 2007; Chaoxin, Da-Wen, & Liyun, 2006; Qiao, Ngadi, Wang, Gariepy, & Prasher, 2007) and notably in the speciality of air-drying process (Lertworasirikul & Tipsuwan, 2008; Goni, Oddone, Segura, Mascheroni, & Salvadori, 2008). The advantage of this class of models lays on simple arithmetic operations with well-known input parameters. However, in many cases, when we want to have an optimum output, the optimal input parameters are unknown. Consequently, the aim of this very relevant work is to develop a strategy to obtain, on-line, the optimum operating conditions in the drying process from artificial neural

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network inverse (ANNi). For the purpose of demonstrating this strategy, two ANN models were taken from literature, that predicts heat and mass transfer during mango and cassava drying.

## 2. Heat and mass transfer prediction using neural networks

Hernández-Pérez et al. (2004) proposed two feedforward networks with one hidden layer, to predict temperature and moisture kinetics on-line (two outputs), in fact during the drying process for mango and cassava. The coefficients of the neural networks (weights  $W_i$ ,  $W_o$  and biases  $b1, b2$ ), the number of neurons in the hidden layer and the number of iterations of the algorithm of optimization were calculated in the training stage, by minimizing a root mean square error of modelling in comparison with experimental data. Hernández-Pérez et al. (2004) used Matlab toolbox for neural networks (Demuth & Beale, 1998), using an algorithm of optimization of Levenberg–Marquardt type, considered by Hagan and Menhaj (1994) as being the most efficient. The optimal models were obtained with three neurons in the hidden layer both for the mango and cassava model (see Fig. 1).

In the Fig. 1, the input parameters are:  $T_a(^{\circ}\text{C})$  air temperature,  $V_a(\frac{\text{m}}{\text{s}})$  air velocity,  $L_v$  thickness (cm),  $t$  time (min) and  $X_a$  air humidity ( $\frac{\text{g water}}{\text{g air dry}}$ ). The output variables are  $\hat{\Psi}$  and  $\hat{U}$ , which represent the moisture and temperature of the product, in dimensionless form.  $X$  and  $X_o$  are the moisture and initial moisture of the product ( $\frac{\text{g water}}{\text{g dry matter}}$ ), respectively,  $X_e$  is the equilibrium moisture ( $\frac{\text{g water}}{\text{g dry matter}}$ ),  $T$  and  $T_o$  are the food and initial food temperature, respectively. The Eqs. (1) and (2) represent the general artificial neural network model for mango and cassava of the Fig. 1.

$$\frac{X - X_e}{X_o - X_e} = \sum_s \left\{ W_{o(1,s)} \cdot \left[ \frac{2}{1 + e^{-2 \left( \sum_k W_{i(s,k)} \cdot \ln(k) + b1_{(s,1)} \right)}} - 1 \right] \right\} + b2_{(1,1)} \quad (1)$$

$$\frac{T - T_a}{T_o - T_a} = \sum_s \left\{ W_{o(2,s)} \cdot \left[ \frac{2}{1 + e^{-2 \left( \sum_k W_{i(s,k)} \cdot \ln(k) + b1_{(s,1)} \right)}} - 1 \right] \right\} + b2_{(2,1)} \quad (2)$$

where  $W_{i(s,k)}$ ,  $W_{o(l,s)}$ ,  $b1_{(s,1)}$  and  $b2_{(l,1)}$  are presented in the Tables 1 and 2 for mango and cassava, respectively.

## 3. Optimum operating conditions using the ANNi

According to proposed ANN model (Eqs. (1) and (2)), it is possible to simulate the temperature and moisture transfer during the

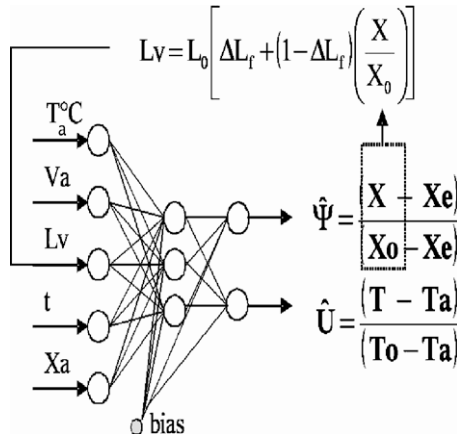


Fig. 1. Structure of the neural network proposed to simulate heat and mass transfer during the drying process.

Table 1

Statistical parameters of the neural network model for mango

With $l = 2, s = 3$ and $k = 5$					
$W_{i(s,k)}$	-0.1035	-0.0665	-0.1367	-7.2518	0.0500
	0.4369	-0.5174	1.7002	-3.2170	8.2998
	0.4172	-0.5266	1.6910	-3.4127	8.3539
$W_{o(l,s)}$		9.2722	5.3779	-4.9553	
		17.5940	1.2053	-1.0138	
			-1.8564		
$b1_{(s,1)}$			1.1365		
			1.2656		
			9.6197		
$b2_{(l,1)}$			17.7911		

Table 2

Statistical parameters of the neural network model for cassava

With $l = 2, s = 3$ and $k = 5$					
$W_{i(s,k)}$	-0.6747	-0.0856	-0.4637	-3.9055	-6.8911
	2.5133	0.4588	-4.0862	2.0404	-2.4127
	-6.7229	2.7800	18.3839	0.1518	-98.4576
$W_{o(l,s)}$		2.8522	-0.2957	0.0556	
		3.7302	-0.1002	0.1021	
			-0.4892		
$b1_{(s,1)}$			-1.1895		
			-0.2923		
			3.1475		
$b2_{(l,1)}$			3.9383		

drying process of mango and cassava when input parameters are well-known. However, in industry for example, it is important to know, the optimum drying time required for a given food product at 70 °C air temperature. Consequently, it is developed a strategy to calculate the optimal parameters which inverts the ANN.

A general neural network is given by

$$y(l) = \sum_s \left\{ W_{o(l,s)} \cdot \left[ \frac{2}{1 + e^{-2 \left( b1_{(s,1)} + \sum_k W_{i(s,k)} \cdot \ln(k) \right)}} - 1 \right] \right\} + b2_{(l,1)} \quad (3)$$

The Eq. (3) can be expressed as Eq. (4):

$$y(l) = b2_{(l,1)} - \sum_s W_{o(l,s)} + \sum_s \left[ \frac{2 \cdot W_{o(l,s)}}{1 + e^{-2 \left( b1_{(s,1)} + \sum_k W_{i(s,k)} \cdot \ln(k) \right)}} \right] \quad (4)$$

Let  $\ln(k=4)$  be the input to be optimized and  $y_{(l=2)}$  the required output. Then Eq. (5) is given as follows:

$$y_{(2)} = b2_{(2,1)} - \sum_s W_{o(2,s)} + \sum_s \left[ \frac{2 \cdot W_{o(2,s)}}{1 + e^{-2 \left( b1_{(s,1)} + W_{i(s,4)} \cdot \ln(4) + \sum_{(k \neq 4)} W_{i(s,k)} \cdot \ln(k) \right)}} \right] \quad (5)$$

An expression is obtained involving the optimum operating conditions, then Eq. (6) is to be optimized:

$$f(x) = b2_{(2,1)} - \sum_s W_{o(2,s)} - y_{(2)} + \sum_s \left[ \frac{2 \cdot W_{o(2,s)}}{1 + e^{-2 \left( b1_{(s,1)} + W_{i(s,4)} \cdot x + \sum_{(k \neq 4)} W_{i(s,k)} \cdot \ln(k) \right)}} \right] \quad (6)$$

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