Neural Network Approaches for Prediction of Drying Kinetics During Drying of Sweet Potato

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ABSTRACT: Drying kinetic of sweet potato was investigated considering different drying conditions. The drying experiments were performed at five levels of drying air temperature of 50-90^oC, together with five levels of air flow velocities of 1.5-5.5 m/s, and also three levels of thickness of 0.5-1.2 cm. A predictive model using artificial neural network was proposed in order to obtain on-line predictions of moisture kinetics during drying of Sweet potato. A three-layer network with tangent sigmoid transfer function in hidden layer and linear transfer functions in the output was used. A feedforward network with two hidden neurons was used. The best fitting with the training data set was obtained with eight neurons in first hidden layer and 4 neurons in second hidden layer, which made possible to predict moisture kinetics (moisture content, drying rate and moisture ratio) with accuracy, at least as good as experimental error, over the whole experimental range. On validation data set, simulation and experimental kinetics test were in good agreement. Comparing the R^2 (coefficient of determination), MRE and STD_R using the developed ANN model it was concluded that the neural network could be used for on-line state estimation of drying characteristics and control of drying processes.

***Keywords**:* Thin layer drying; Neural networks; Feedforward networks; Sweet potato

Introduction

Sweet potato (*Ipomoea batatas* Lam.) is an important source of carbohydrate for people in Asia. Since its root part is also rich in B-carotene, food fibre, and potassium ion, etc., sweet potato is widely used in ready-to-eat foods, etc. The possibility of using Sweet potato starches in noodles and other wheat-based foods has been investigated by different researches (Noda *et al*., 2006). Sweet potato starch can be used as an ingredient in bread, biscuits, cake, juice and noodles (Zhang & Oates, 1999).

Air-drying is an essential procedure in food processing industries. On-line state estimation and control of air drying operation requires the mathematical description of food temperature and moisture evolution during the process. The dynamics of food drying process involves simultaneous heat and mass transfer, where water is transferred by diffusion from inside of the food material towards the air-food interface, and from the interface to the air stream by convection. Heat is transferred by convection from the air to the air-food interface and by conduction to the interior of food (Balaban & Piggot, 1988; Karathanos *et al.,* 1990, Kiranoudis, *et al.,* 1993). This phenomenon has been modeled with different levels of complexity. Existing models do not permit in adequate control of the air drying process in industrial applications. Physical dynamic models, considering the complexity of the process, usually result in coupled non-linear differential equations with partial derivatives which are very time consuming. However, these equations can be simplified (Sablani *et al*., 2005 and Hernandez, 2009), although not taking into account the complexity of the process, and still contain ordinary non-linear differential equations that take too long to simulate for control applications (Trelea *et al*., 1997). Empirical models representations approximate the drying kinetics by several line segments (Daulin, 1982), high order polynomials and neural networks, but require only a limited number of simple arithmetic operations for simulation, and can be easily incorporated in control software.

Neural networks are recognized as good tools for dynamic modeling, and have been extensively studied since the publication of the perceptron identification methods (Rumelhart *et al*., 1986). The interest of such model includes the modeling without any assumptions about the nature of underlying mechanism and their ability to take account non-linearities and interactions between variables (Bishop, 1994). Recent results establish that it is always possible to identify a neural model based on the perceptron structure, with only one hidden layer, for either steady state or dynamic operations. An outstanding feature of neural network is the ability to learn the solutions of problems from a set of examples, and to provide smooth and reasonable interpolations for new data. Also, in the field of food process engineering, it is a good alternative for conventional empirical modeling based on polynomial, and linear regressions. For food processes, the application of neural network keeps on expanding (Erenturk and Erenturk, 2007, Torrecilla *et al.,* 2007, Assidjo *et al*., 2008, Lertworasirikul and Tipsuwan, 2008, Huang & Mujumdar, 1993).

In this work, an attempt has been made to predict the drying kinetics of sweet potato drying with a wide range of independent variables and to test the importance and efficiency of neural networks to model and predict the moisture transfer during air drying of food stuffs. The model validation was made with experimental drying data of sweet potato cubes.

2. MATERIALS AND METHODS

2.1 Neural Network Systems

Neural networks are composed of simple elements operating in parallel. As in nature, network function is determined largely by the connections between the neurons, each connection between two neurons has a weight coefficient attached to it. The neuron is grouped into distinct layers and interconnected according to a given architecture. The standard network structure for function approximation is the multiple layer perceptron (or feed forward network). The feed forward network often has one or more hidden layers of sigmoid neurons followed by an output layer of linear transfer functions to allow the network to learn non-linear and linear relationship between input and output vectors. The linear output layer lets the network produce values outsides the range -1 to +1 (Limin, 1994). For multiple-layer networks we use the number of the layers to determine the superscript on the weight matrices. The appropriate notation is used in two-layer networks. A simple view of the selected network structure and behavior is given Fig. 1.

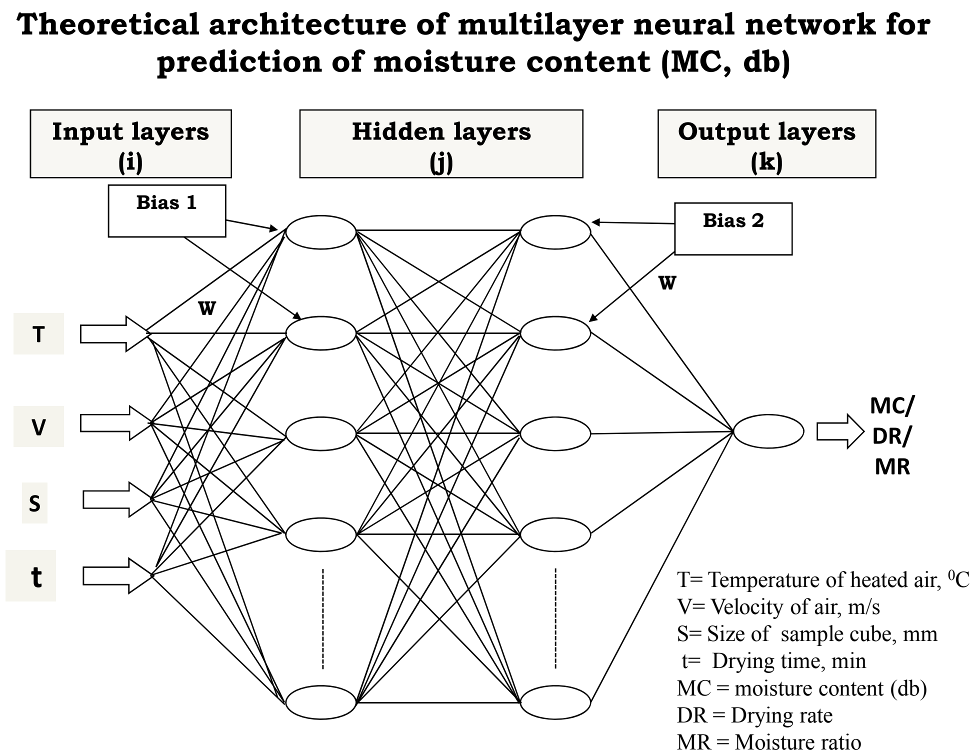

Fig.1. Topological Structure of Artificial Neural Network, k = number of inputs; ln = inputs; Out = output, W = weights and b= biases.

The number of neurons in the input and output layers are given by the number of input and output variables in the process under investigation. In this work, the input layer consists of four variables in the process air temperature (T), air velocity (V), sample thickness (s) and time of drying (t) and the output layer contains one variable; Moisture content (d.b.). The optimal number of neurons in the hidden layer n_s is difficult to specify, and depends on the type and complexity of the task, usually determined by trial and error. Each neuron in the hidden layer has a bias b, which is added with the weighted inputs to form the neuron input n. This sum, n, is the argument of the transfer function f :

$$n = Wi_{\{1,1\}} ln_1 + Wi_{\{1,2\}} ln_2 + \ldots\ldots\ldots\ldots + Wi_{\{1,k\}} ln_k + b \qquad \ldots(1)$$

The coefficients associated with the hidden layer are grouped into matrices Wi1 (weights) and b1 (biases). The output layers computes the weighted sum of the signals provided by the hidden layer, the associated coefficients are grouped into matrices Wo_3 and b_3. Using the matrix notation, the network output can be given by Eq. (2)

$$Out = f' \{Wo_3 \times f\,(Wi_2 \times 1n + b_2) + b_3\} \qquad \ldots(2)$$

Hidden layer neurons may use any differentiable transfer function to generate their output. In this work, a tangent sigmoid transfer function and linear transfer function were used for f and f', respectively. The equation of network coefficient (weight and biases) is given by the equation (2)

2.2 Learning Algorithm

A learning (or training) algorithm is defined as a procedure that consists in adjusting the coefficients (weight and biases) of a network, to minimize an error function (usually a quadratic one) between the network outputs for a given set of inputs and the right outputs already known. If smooth non-linearities are used, the gradient of the error function can be easily computed by classical back propagation procedure (Rumelhart *et al.,* 1986).

Previous learning algorithms used this gradient directly in a steepest descent optimization, but recent results show that second order methods are far more effective. In this work, the Levenberg-Marquardt, optimization procedure in the Neural Network Toolbox of Matlab was used. The algorithm of Levenberg is an approximation of Newton's methods, this algorithm was designated to approach second order training speed without having to compute the Hessian matrix (Martin *et al.,* 1994). Despite the fact that computations involved in each iteration are more complex than in the steepest descent case, the convergence is faster, typically by a factor of 100. The root mean square error (RMSE) between the experimental values and network predictions were used as a criterion of model adequacy.

2.3 Database Preparation

Experimental data were obtained from drying of sweet potato cubes having thickness 5, 8 and 12 mm at five different air temperatures (50, 60, 70, 80 and 90^{o}C) and five air velocities (1.5, 2.5, 3.5, 4.5 and 5.5 m/s) with a time 0 - 220 min for each kinetics. It resulted in around 1400 experiment data. Experimental data were split into learning and test databases to obtain a good representation of the situation diversity. The inputs (In) of the network were air temperature (T)/90, air velocity (V)/5.5, cube thickness (d)/12 and time (t)/220; the outputs (out) was moisture content (db).

Food moisture evolution during drying was calculated by sample weight loss of the product using weight balance with accuracy $\pm$ 0.0001g (mettle Germany). The learning database was obtained to optimize the neural network and the test database was reserved for validation of the predictive capability of the model.

3. RESULTS AND DISCUSSION

In the first attempt, ANN models were trained using data set with four inputs (air temperature, air velocity, cube thickness, time and one output MC (dm/dt or MR). The configuration of the ANN model was varied. The learning rate which determines the amount of weight changes during series of iterations to bring the predicted value within an acceptable range of the observed values, were adjusted between 0.01 and 0.08 with the hidden neurons kept constant at 8 in first hidden layer and 4 neurons in second hidden layer on trial basis. Preliminary trials indicated that higher learning rates (η) produced poorly developed models which agree with findings of **Chhaya and Rai (2008).** After these trial runs, the learning rate was fixed at 0.05 and momentum at 0.9. During training the neural network weights were initialized in order to obtain the smallest possible predicting error, simulations were performed 2500 times with frequency of progress of 50 (Fig. 2). A simple propagation network using the Levenberg-Marquarardt for training the network was found to be very effective to generalize and predict the moisture of the final dried product. The minimum value of root mean square error (RMSE) in the range of 0.00052 to 0.00092 was also reached well within that number in all the three drying kinetics. These observations were in good agreement with previous research workers **(Assidjo *et al*. 2008 and Chhaya and Rai, 2008).**

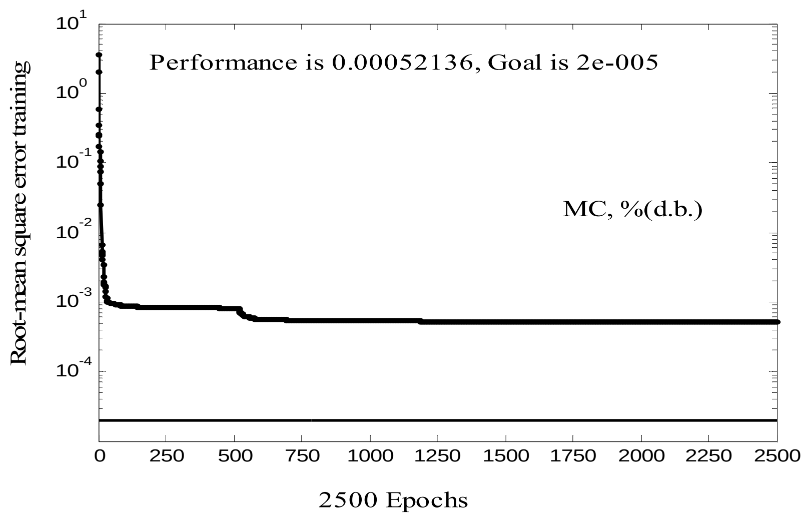

Fig. 2 Variation of root-mean square error training with iteration number (epochs)

Fig. 2 indicates the trial RMSE values against the iteration number for moisture content. The topology which gave the minimum error in minimum number of iterations during the training of the ANN was selected. The various ANN topology along with coefficient of determination and other associated statistics are presented in Table 1. Total of 30 configurations were performed in order to search the optimal topology.

Table 1. Prediction of Moisture content (MC) db,% for Sweet potato Samples

No. of hidden layer	Neurons in 1st hidden layer	Neurons in 2nd hidden layer	M.C. , %				
			MAE	MRE, %	STD_A	STD_R	R^2
1	2	-	0.017	12.890	0.017	0.133	0.996
1	4	-	0.015	11.483	0.016	0.125	0.997
1	6	-	0.013	10.896	0.014	0.135	0.997
1	8	-	0.013	12.623	0.014	0.180	0.998
1	10	-	0.013	13.967	0.013	0.210	0.998
2	2	2	0.015	10.564	0.016	0.119	0.997
2	2	4	0.015	11.773	0.016	0.140	0.997
2	2	6	0.014	10.880	0.016	0.130	0.997
2	2	8	0.014	10.327	0.015	0.134	0.997
2	2	10	0.014	10.252	0.016	0.134	0.997
2	4	2	0.013	12.292	0.014	0.161	0.997
2	4	4	0.012	10.367	0.013	0.134	0.997
2	***4***	***6***	0.011	11.001	0.011	0.156	0.998
2	4	8	0.014	14.214	0.014	0.191	0.997
2	4	10	0.011	10.201	0.014	0.143	0.999
2	6	2	0.012	10.735	0.012	0.140	0.998
2	6	4	0.014	12.500	0.015	0.277	0.997
2	6	6	0.011	12.358	0.011	0.194	0.998
2	6	8	0.010	11.085	0.010	0.182	0.999
2	6	10	0.013	15.516	0.013	0.223	0.999
2	8	2	0.011	10.595	0.011	0.127	0.998
2	***8***	***4***	***0.009***	***8.258***	***0.010***	***0.114***	***0.999***
2	8	6	0.010	9.961	0.011	0.160	0.999
2	8	8	0.010	10.416	0.015	0.153	0.998
2	***8***	***10***	0.009	11.446	0.011	0.212	0.999
2	10	2	0.012	10.795	0.012	0.140	0.998
2	10	4	0.012	12.614	0.012	0.193	0.998
2	10	6	0.011	12.954	0.018	0.790	0.997
2	10	8	0.010	10.874	0.010	0.186	0.999
2	10	10	0.009	10.942	0.011	0.211	0.999

3.1 Verification of the ANN Models

The prediction performance of all the ANN models (MC, dm/dt or MR) was validated using a data of 20 % cases, which were not used in the initial training of the ANN models. The simple ANN model (2 hidden neurons) predicted MC with a mean relative error of 8.258, a standard deviation on relative error of 0.114 and a coefficient of determination of 0.9987 as presented in Table 2.

Table 2 Architecture of ANN with Minimum MRE for all Combinations in hot air drying of treated sample

Architecture	MC (% db)	dm/dt (Drying rate)	MR
No. of hidden layer	2	2	2
No. of neuron first hidden layer	8	8	4
No. of neuron in second hidden layer	4	10	6
MAE	0.009	0.0157	0.0061
STD_A	8.258	17.355	9.4725
MRE	0.010	0.0301	0.0079
STD_R	0.114	0.2470	0.1602
R^2	0.9987	0.9930	0.9984

The ANN model with 2 hidden neurons predicted dm/dt (drying rate) with a mean relative error of 17.355, a standard deviation of relative error of 0.2470 and a coefficient of determination of 0.9930. The MRE, STD_R and coefficient of determination in prediction of moisture ratio (MR) were 9.4725, 0.1602 and 0.9984 respectively. **Lertworasirikul and Tipsuwan (2008)** predicted moisture content and water activity of semi-crackers cassava from a hot air drying process in a tray dryer using one hidden layer having nine nodes and logarithmic sigmoid transfer function and reported that the mean squared error and regression coefficient (R^2) was 0.0034 and 0.9910 respectively, which was in close agreement with the findings of present study. Each data set was divided into two groups, consisting of 80% for training and 20% for testing. During training, the data set was used to determine the optimum number of hidden layers, neurons per hidden layer that gave the best predictive power. Architecture of artificial neural network was hidden layers 1 and 2 and neurons 2-10 hidden layer. Each combination of hidden layers and neurons per hidden layer was trained. Relative mean square error (MAE), standard deviation of MAE (STD_A), percentage of relative mean square error (% MRE) and standard deviation of % MRE (STD_R) and R^2 along with number of hidden layers and neurons in each hidden layer were computed. It was observed that the number of hidden layers, and neurons per hidden layer, that yielded minimum error was different for each drying technique. Table 3. revealed the detailed ANN structure for all combinations of data set of blanched and treated and blanched samples hot air drying. A large number of hidden layers are not required to lower the error if there is enough number of neurons **(Torrecilla *et al.*, 2007).** The best prediction for most of the data set contained two hidden layers. ANN developed for combined drying data had slightly higher error than individual conditions.

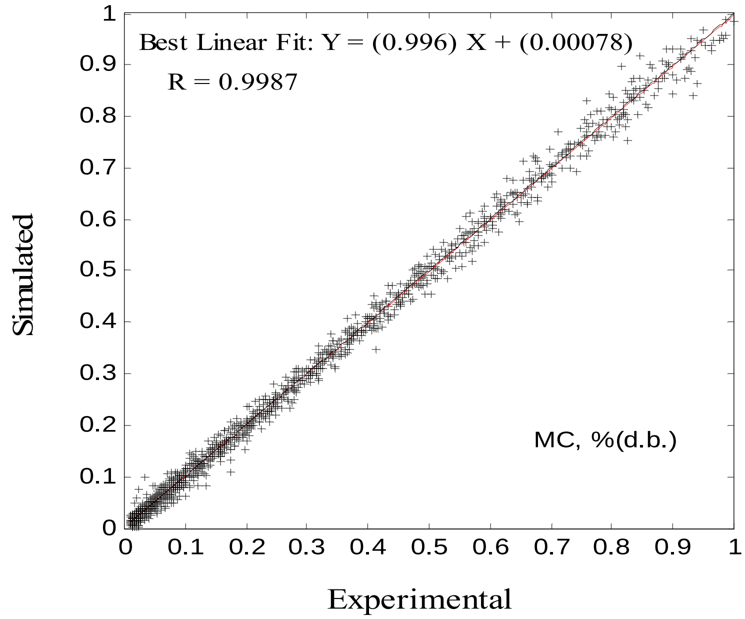

Fig. 3 Correlation between predicted and experimental data for the treated sample

Plots of experimentally determined moisture content, drying rate and moisture ratio versus ANN simulated values for all combined data shown in Fig. 3. The correlation coefficients were greater than 0.99 in all cases. For all combined data set for blanched and treated samples, the R^2 was found 0.9987, 0.9930 and 0.9984 for moisture content, drying rate and moisture ratio, respectively and for blanched samples, the R^2 were 0.9984, 0.9917 and 0.9987. This shows that the ability of ANN to predict moisture content, drying rate and moisture ratio was very good. These observations are consistent with previous research workers **(Hernandez-Perez *et al.*, 2004)** on Cassava in which correlation coefficients between the predicted and observed moisture content was more than 0.9998. The system equations representing the ANN for predicting moisture content, drying rate and moisture ratio are given in Table 3.

The equation shows the input, transfer function and relative weights and biases of each node. The equations can be used in computer program to predict the moisture content, drying rate and moisture ratio of sweet potato cubes **(Islam *et al.*, 2003).** The minimum and maximum error involved between actual and predicted values were 0.009-0.017, 0.0157-0.0330 and 0.0061-0.0212 for moisture content, drying rate and moisture ratio for blanched and treated sample respectively and 0.009-0.017, 0.0181-0.0266 and 0.0082-0.0178 for blanched samples respectively. It is evident that the model was successful in predicting the experimental drying kinetics. This shows the importance of the artificial neural network to simulate the drying curves of foodstuff. These models are not complex because simulation is realized by simple arithmetic operations, and therefore, they can be used for on-line estimation in air drying processes for industrial applications **(Erenturk and Erenturk, 2007).**

Table 3 ANN model for prediction of Moisture Content (db, %)

Input variables:
X1 = Temperature, ^{o}C
X2 = Air velocity, m/s
X3 = Cube size, cm
X4 = Time, min
First hidden layer
H1 = tansig[(4.2554*X1+0.5461*X2+3.7369*X3+2.509*X4)-0.84272]
H2 = tansig[(3.8593*X1+0.8758*X2+2.5884*X3+0.9339*X4)-6.8799]
H3 = tansig[(-4.8827*X1+2.5006*X2-6.0765*X3-15.589*X4)-5.3058]
H4 = tansig[(0.2422*X1+0.5035*X2+0.7358*X3-1.0578*X4)-1.0176]
H5 = tansig[(-2.1996*X1+11.3534*X2+1.8041*X3+4.5596*X4)-3.9677]
H6 = tansig[(0.3429*X1-0.3593*X2-0.2657*X3-1.111*X4)-0.6475]
H7 = tansig[(-0.0215*X1+0.0277*X2+0.0179*X3+3.1194*X4)+5.1817]
H8 = tansig[(14.6736X1-31.4342*X2+14.8288*X3+12.956*X4)+12.0315]
Second hidden layer
G1= tansig[(0.1817*H1-0.8615*H2+0.0546*H3-0.4916*H4-0.0723*H5-0.9517*H6-10.1522*H7+0.0308*H8)+9.5811]
G2 = tansig[(21.5471*H1+8.1645*H2+2.8121*H3-19.1811*H4-2.225*H5-7.5634*H6+8.5984*H7-24.5878*H8)+14.8178]
G3 = tansig[(-0.9151*H1-0.020*H2+0.8406*H3-1.2553*H4-20.8199*H5-4.6587*H6+4.0193*H7+0.5970*H8)+15.8368]
G4 = tansig[(-0.1986*H1+0.8074*H2-0.0559*H3+0.4480*H4+0.0616*H5+1.0722*H6-21.7917*H7-0.0065*H8)+22.3392]
MC (output) = purelin[(1.5106*G1+0.0208*G2-0.0394*G3+1.7508*G4)-0.7470]

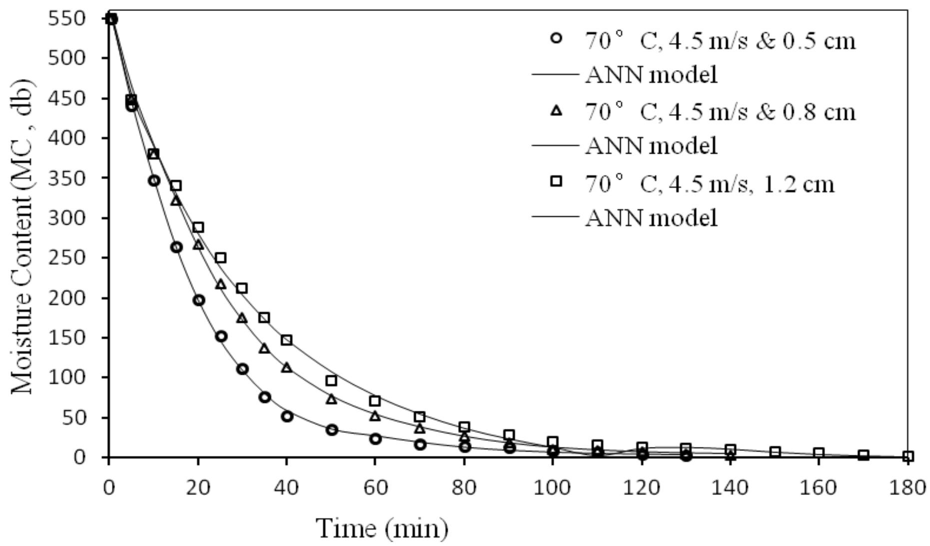

Fig. 4 Experimental data and simulated moisture ratio curves generated with proposed model in the drying kinetics of Sweet potato.

Fig. 4 depicts the ability of the models to predict drying kinetics at different thickness, temperature and air velocities for a narrower validity range (*e.i.*, 70^{0}C, 4.5 m/s & 0.5, 0.8 and 1.2 cm). In all cases, the drying rate decreased continuously throughout drying period (Diamante and Munro, 1993).

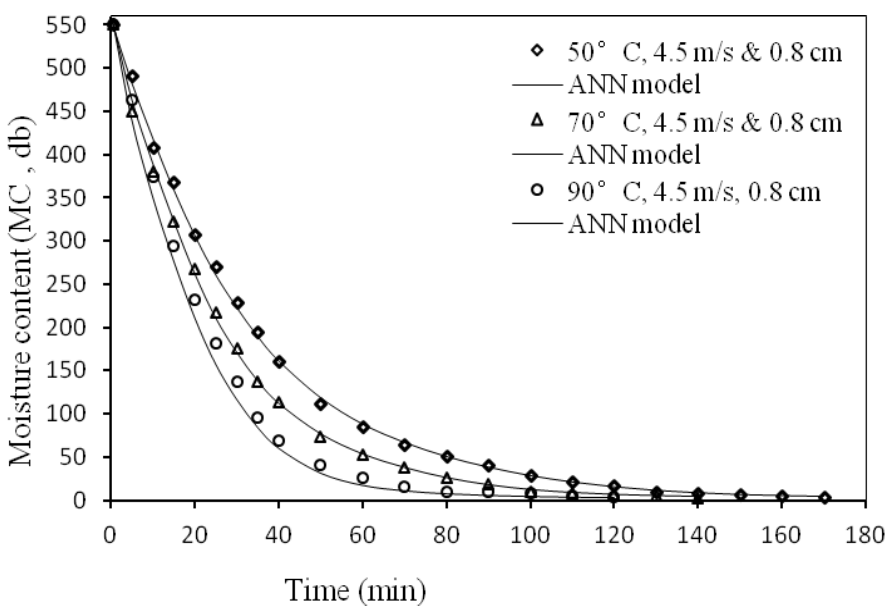

Fig. 5 Experimental data and simulated curves generated with proposed model in the drying kinetics of Sweet potato.

The moisture content Fig. 5 shows some moisture content simulated results and experimental data obtained by the test database for drying air temperatures; 50-90^{0}C for 4.5 m/s and 0.8 cm size). It is evident that the model was successful in predicting the experimental drying kinetics. This shows the importance of the artificial neural network to simulate the drying curves of foodstuff. These models are not complex because simulation is realized by simple arithmetic operations, and therefore, they can be used for on-line estimation in air drying processes for industrial applications.

CONCLUSIONS

The applicability of an ANN to model a hot air dryer was discussed and illustrated with numerical simulations and experimental data involving different conditions operation. The results obtained in this work showed that the proposed ANN could be successfully applied to model convective hot air dryer for drying of sweet potato cubes. The proposed neural network model provided more than 0.05% accuracy in the estimation of moisture content. The ANN showed suitable accuracy and degree of generalization to predict the moisture content of the dried solid when the ANN was trained with a learning coefficient of 0.5 and 2500 iterations. Values larger than these ones did not improve significantly the predictions of the ANN. It also demonstrated that the proposed neural network model not only minimized R^2, but also removed dependence on the mathematical model. As a result, neural network model introduced here was successful in predicting the experimental drying kinetics. This shows that the importance of the artificial neural network model is not complex since the estimation is realized by simple arithmetic operations. Hence, the artificial neural networks can be used for the on-line estimation of drying kinetics and also controlling the drying processes in industrial operations successfully.

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