

## Modelling the convective drying process of pumpkin (*Cucurbita moschata*) using an artificial neural network

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### Article history

Received: 21 July 2016  
Received in revised form:  
14 September 2016  
Accepted: 16 September 2016

### Abstract

This study investigated the drying kinetic of pumpkin under different drying temperatures (50, 60, 70 and 80°C), samples thickness (3, 4, 5 and 7mm), air velocity (1.2m/s) and relative humidity (40 - 50%). Kinetic models were developed using semi-theoretical thin layer models and multi-layer feed-forward artificial neural network (ANN) method. The Hii *et al.* (2009) semi-theoretical model was found to be the most suitable thin layer model while two hidden layers with 20 neurons was the best for the ANN method. The selections were based on the statistical indicators of coefficient of determination ( $R^2$ ), root mean square error (RMSE) and sum of squares error (SSE). Results indicated that the ANN demonstrated better prediction than those of the theoretical models with  $R^2$ , RMSE and SSE values of 0.992, 0.036 and 0.207 as compared to the Hii *et al.* (2009) model values of 0.902, 0.088 and 1.734 respectively. The validation result also showed good agreement between the predicted values obtained from the ANN model and the experimental moisture ratio data. This indicates that an ANN can effectively describe the drying process of pumpkin.

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### Keywords

Mathematical modelling  
Thin layer drying  
Pumpkin  
Artificial neural network

### Introduction

The food, agro-allied, pharmaceutical and chemical industries are becoming increasingly interested in the use of fruits and vegetables, containing high amount of carotenoids and other antioxidants, as ingredients either wholly or partly in the production of food supplements, food products, cosmetics and drugs. Pumpkin (*Cucurbita moschata*) has been widely used as an ingredient in a number of food, pharmaceutical and bio-product production processes. It is rich in carotenes, minerals and pectin (Krokida *et al.*, 2003). The chemical composition is also rich in antioxidants and vitamins, which makes pumpkin a source of good health and general utilisation (Murkovic *et al.*, 2005). However, due to its delicate nature, pumpkin requires more effective preservation methods to increase its shelf life (Doymaz, 2007).

Drying is one of the oldest methods of food and agricultural products preservation (Alonge and Onwude, 2013) which keeps the food in a stable and safe condition, thereby extending shelf life and maintaining quality attributes (Duan *et al.*, 2010; Mujumdar and Law, 2010). For most industrial applications, convectional hot air drying is widely

applied. Hot air drying involves the uniform distribution of hot air on a material undergoing dehydration and can negatively affect important properties of the food products, such as the nutritional properties and phytochemical properties. Thus, the determination of suitable drying model, drying conditions and the determination of the optimum operating parameters are indispensable in achieving great quality along with minimum product cost with maximum yield (Rodríguez *et al.*, 2014).

Artificial neural networks (ANN) are computational tools, which are also seen as a complex tools for complex systems and dynamic modelling. They are inspired by the biological neural system as a useful statistical tool for nonparametric regression. One advantage of ANN over conventional models (such as the empirical model) is the increased flexibility, reduced assumptions, online non-destructive measurement and tolerance of incomplete or noisy data (Omid *et al.*, 2009; Rodríguez *et al.*, 2014). The structure of a neural network is in form of interconnected layers. Haykin (1999) classified an ANN in three groups of structures based on their connection. These are the single layer feedforward network, the multi-layer feedforward network and the recurrent network.

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Multi-layer feed forward network is widely used in the modelling of agricultural and food systems. This class of feedforward neural networks has an input layer ( $n$ ), an output layer ( $m$ ) and one or more hidden layers ( $h$ ) (Omid *et al.*, 2009). The number of neurons in the input and output layers is representative of the amount of independent variables (input) and dependent variables (output) respectively. A multilayer ANN model with three inputs (concentration of osmotic solution, temperature, and contact time) was used to predict the outputs (drying time, colour, texture, rehydration ratio, and hardness) of the osmo-convective drying of blueberries (Chen *et al.*, 2001). Similar multilayer models have been reported for the prediction of the physical properties of osmotically dehydrated pumpkin (Zenoozian *et al.*, 2007).

Many thin layer drying models have been proposed to describe the drying process of fruits and vegetables (Onwude *et al.*, 2016a). The widely applied categories of these models are the theoretical, semi-theoretical and empirical models (Akpınar, 2006; Doymaz, 2007; Erbay and Icier, 2010; Guiné *et al.*, 2011). Amongst these 3, the semi theoretical and theoretical models have been reported to be the most applicable. These categories of models are generally developed based on assumptions of geometry, mass diffusivity and conductivity of food products, and some do not always give accurate results (Ozdemir and Devres, 2000; Erbay and Icier, 2010; Onwude *et al.*, 2016a).

A great deal of research have been reported in literatures concerning the thin layer modelling of the drying process of different agricultural, biological and food products such as kiwifruits (Mohammadi *et al.*, 2008; Darıcı and Şen, 2015), apple (Zarein *et al.*, 2013), red pepper ( Akpınar *et al.*, 2003; Di and Crapiste, 2008; Vega-Gálvez *et al.*, 2008) and pumpkin ( Doymaz, 2007; Hashim *et al.*, 2014; Onwude *et al.*, 2016b). However, there are less information on new modelling approach such as Artificial Neural Network (ANN) in describing the drying behaviour or ways to analyse the drying experimental data of fruits and vegetables, in order to help advance the science. In general, ANN modelling can be used as a potential alternative to empirical and theoretical thin layer models in the drying of fruits and vegetables. ANN has been successfully applied in modelling and optimizing the drying processes of fruits and vegetables such as tomato (Movagharnejad and Nikzad, 2007), carrot (Erenturk and Erenturk, 2007), eggplant (Bahmani *et al.*, 2015), onion (Jafari *et al.*, 2015) and pepper (Jafari *et al.*, 2016). Consequently, ANN techniques can be applied in

predicting the drying kinetics of pumpkin during hot air drying. It can help in the evaluation of drying parameters in real conditions, the optimization of processing condition and the increase on the overall drying efficiency. However, there is no report on the application of ANN technique in modelling the drying kinetics of pumpkin (*Cucurbita moschata*) in a convective hot air dryer.

The objective of this study is to evaluate the feasibility of applying multilayer ANN modelling as a non-destructive technique in describing the drying behaviour of pumpkin under different drying conditions and to compare the results of an ANN model with thin layer mathematical models.

## Materials and Methods

### Sample preparation

The *Cucurbita moschata* variety of pumpkin fruits were purchased locally from wholesalers in Malaysia and stored in a cold room at a temperature of  $10 \pm 1^\circ\text{C}$  during the entire drying experiments which lasted for 14 days. The samples were selected based on same physical appearance (size, colour and shape). A total of 48 samples of pumpkin fruits were used in the experiments. The ANSI/ASAE oven method was used to determine the average initial moisture content of the samples. The average initial moisture content was found to be 6.2 (dry basis).

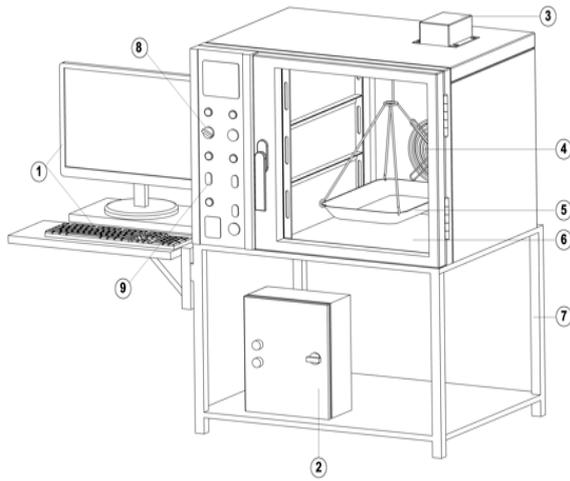
### Drying experiments

Before each drying experiments, the pumpkin samples were selected, hand peeled, washed in running water and the pulp sliced into different dimensions. Subsequently, several drying experiments were conducted at constant temperatures of 50, 60, 70 and  $80^\circ\text{C}$  and an air velocity of 1.2 m/s. The sample slice thickness of 3, 4, 5 and 7 mm (uniform width of 20 mm and length 30 mm) was used and the relative humidity values was within the range 40 to 50% throughout the experiments. A total of 12 experimental runs were carried out with three replications and the average values were used for the moisture ratio estimation. In every experiment, the drying process continued until there was no further change in the masses of two consecutive measurements.

### Drying equipment

A locally designed and fabricated convective dryer, fully automated, was used for the drying experiments (**Figure 1**). Details of the dryer used has been reported by Onwude *et al.* (2016b).

Figure 1. Schematics of the hot air oven (1= system unit; 2=



control panel; 3= load cell; 4= dryer fan; 5= dryer tray; 6= drying chamber; 7= dryer support; 8= dryer switch button; 9=air velocity switch button)

**Mathematical modelling**

Selected thin layer models (Page, Modified page, Henderson and Pabis, Two-term and Hii *et al.* models) were fitted to the experimental data obtained for the four different temperatures, sample thickness and drying time in the form of the moisture ratio (MR) versus time (Hii *et al.*, 2009; Vega-Galvez *et al.*, 2009; Chayjan *et al.*, 2013; Chen *et al.*, 2013; ANSI/ASAE 2014; Hashim *et al.*, 2014):

**Artificial neural network (ANN)**

The goodness of fit of the thin layer models and the ANN models to the experimental data was evaluated using the coefficient of determination ( $R^2$ ), the sum of squares error (SSE) and root mean square error (RMSE) such that the higher the value of  $R^2$  and the lower the SSE and RMSE value, the better was the goodness of fit (Rayaguru and Routray, 2012; Tahmasebi *et al.*, 2014). They are computed mathematically as:

$$R^2 = 1 - \frac{\sum_{i=1}^N (MR_{pre,i} - MR_{exp,i})^2}{\sum_{i=1}^N (MR_{pre} - MR_{exp,i})^2} \tag{1}$$

SSE is also known as the sum of squares error, which measures the differences between each observation and the predicted data from the fit. It is the total deviation of the response values from the fit to the response values. Mathematically, it can be written as:

$$SSE = [\sum_{i=1}^N w_i (x_i - \hat{x}_i)^2] \tag{2}$$

$$RMSE = \left[ \sqrt{\frac{\sum_{i=1}^N ((x_{iobs} - \hat{x}_{ipre})^2)}{N}} \right] \tag{3}$$

where  $MR_{pre,i}$  is the *ith* predicted moisture ratio,  $MR_{exp,i}$  is the *ith* experimental moisture ratio, while  $N$  is number of observations. Also,  $x_{iobs}$  is the observed data value and  $\hat{x}_{ipre}$  is the predicted value from the fit,  $w_i$  is the weighting applied to each data point, usually  $w_i = 1$ .

A multi-layer feed forward network structure with three input parameters (temperature, thickness and time), one output parameter (moisture ratio) and 1-2 hidden layers was trained using the moisture ratio data. A back-propagation algorithm was used in training of the model and a hyperbolic-tang transfer function was used in all cases. The thin layer experimental data was used for the neural network training. The input and output data was divided into two parts: 70% of the data for training and the remaining 30% of the data for testing and validation, which was randomly selected. The chosen hidden layer architectures were [4], [8], [10], [4, 4], [8, 8] and a [10, 10] matrix, where [8, 8] represents the two hidden layers with eight neurons each (Figure 2).

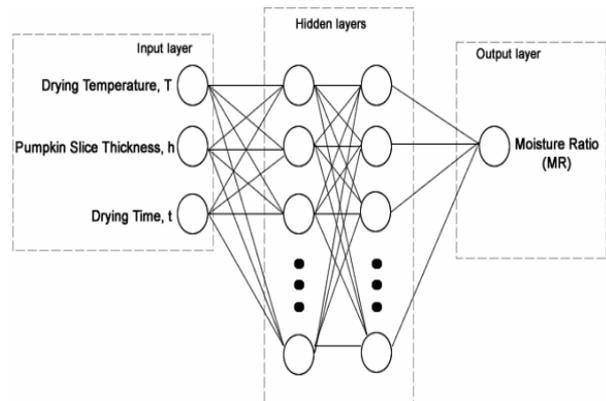


Figure 2. The selected multi-layer neural network scheme

The neural network toolbox of Matlab software version R2014a was used to train the ANN network, the number of hidden layers and neurons, the learning rule, the learning coefficient, the random number seed and the transfer/activation function. The performance of the various ANN configurations was compared using statistical parameters such as  $R^2$ , SSE and RMSE. The performance of the optimal neural network was then validated using a small data set not used in the training procedure. The optimisation algorithm used for training was the Levenberg-Marquardt Backpropagation Transfer function choice as given in Equation 4:

$$\text{Logarithmic sigmoid, logsig}(w, x) = 1/(1 + e^{-(w \cdot x)}) \quad (4)$$

where  $x$  is the input vector and  $w$  is the adjustable weight vector. As such, the prediction ability was tested. Thereafter, the network weights and coefficients associated with the optimal ANN model were simulated so that it could be used for future predictions without the need of the neural network tools for the specific drying conditions.

## Results and Discussion

Table 1 presents the results of fitting the selected thin layer models against the experimental data. From the statistical results, it can be seen that the best model, which has the highest  $R^2$  and lowest SSE and RMSE values, is the Hii *et al.* model. This model has been reported as the best thin layer model for predicting the drying kinetics of pumpkin (Onwude *et al.*, 2015; Onwude *et al.*, 2016b).

**Table 1** Statistical results of thin layer theoretical models

Models	SSE	RMSE	$R^2$
Page Model*	1.762	0.0885	0.902
Modified Page	1.859	0.0909	0.896
Henderson and Pabis	1.851	0.0907	0.897
Two Term Model	1.774	0.0890	0.901
Hii <i>et al.</i> Model*	1.734	0.0884	0.902

\*models with best fitting results

Furthermore, the statistical results associated with training, validation and testing of the multi-layer feed forward network structure of pumpkin drying experimental data are shown in Table 2. During training, the data sets were used to evaluate the optimum number of hidden layers and neurons for multi-layer neural network modelling in order to determine the best predictive power. The results showed that the architecture with 2 hidden layers and 20 neurons [10, 10], gave the best results as compared to those of 1 hidden layer (4, 8 and 10 neurons) and 1 hidden layers (8 and 16 neurons) respectively.

In addition, the networks were found to be

susceptible to the number of neurons in their hidden layers. Consequently, fewer neurons led to under fitting, while too many neurons contributed to over fitting. From the results of Table 1 and Table 2, it can be seen that the ANN model is more accurate than the theoretical thin layer models with  $R^2$ , RMSE and SSE values of 0.992, 0.036 and 0.207 respectively as compared to those of the Hii *et al.* model ( $R^2 = 0.902$ , RMSE = 0.0884 and SSE = 1.734). Mokhtarian *et al.* (2014) reported that the Newton model gave better results compared with other thin layer models during the drying of pumpkin cubes. However, results of modelling using ANN showed that logsig activation function with 18 neurons in first hidden layer performed better in predicting the MR of pumpkin during hot air drying. Similar results on the application of ANN in predicting the drying kinetics of pumpkin (*Cucurbita pepo*) during osmotic dehydration, showed that logsig activation function with 2 hidden layers and 30 neurons adequately predicted the moisture changes (Zenoozian *et al.*, 2007). ANN with 2 hidden layers have also been successful in predicting the drying behaviour of other fruits and vegetables. Nadian *et al.* (2015) reported that a multi-layered perceptron (MLP) ANN algorithm with 2 hidden layers and 35 neurons were best in predicting the moisture ratio of apple slices during hot air drying. Ghaderi *et al.* (2012) compared the performance of thin layer models with ANN model in predicting the drying kinetics of mushroom during microwave-vacuum drying. They concluded that the ANN model with 2 hidden layers and 30 neurons successfully predicted the drying kinetics of mushroom. The results of their comparison with thin layer models showed that the artificial neural networks performed better than mathematical models in predicting moisture ratio and drying rate of mushroom slices. Similar results on the performance of ANN models over thin layer models in predicting the moisture ration and drying rate of other fruits and vegetables have been reported such as bergamot (Sharifi *et al.*, 2011), eggplant (Bahmani *et al.*, 2015), onion (Jafari *et al.*, 2015) and pepper (Jafari *et al.*, 2016).

**Table 2** Statistical results for multi-layer neural network models

No.hidden layers	No. Neurons	Training			Validation			Test		
		SSE	RMSE	$R^2$	SSE	RMSE	$R^2$	SSE	RMSE	$R^2$
1	4	0.804	0.071	0.970	0.352	0.102	0.928	0.108	0.056	0.979
1	8	0.821	0.072	0.967	0.123	0.060	0.972	0.147	0.066	0.981
1	10	1.025	0.081	0.959	0.310	0.096	0.965	0.078	0.048	0.985
2	4, 4	0.900	0.076	0.967	0.345	0.101	0.927	0.131	0.062	0.962
2	8, 8	0.335	0.046	0.986	0.142	0.064	0.976	0.052	0.040	0.993
2*	10, 10*	0.207	0.036	0.992	0.063	0.043	0.991	0.184	0.074	0.999

\*best model based on statistical indicator

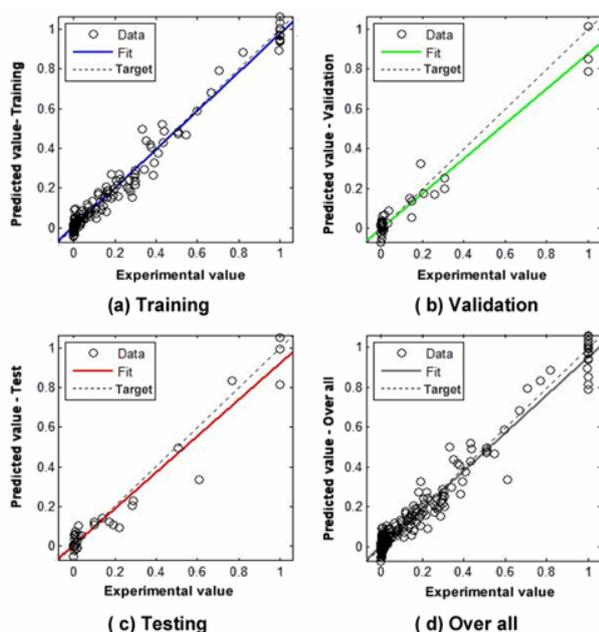


Figure 3. Predicted vs experimental data of pumpkin (*Cucurbita moschata*) using a multi-layer neural network (2 hidden layers, 20 neurons)

Figure 3(a-d) shows the correlation between the experimental and predicted values by an ANN neural network. The values of the training, validation, testing and overall dataset fitted along a linear line. The results demonstrated good agreement between the predicted and the experimental values of moisture ratio. Thus, the ANN model was able to accurately predict the moisture ratio of pumpkin during convective hot air drying.

## Conclusion

In this study, the feasibility of using artificial neural network as a modelling tool for predicting the drying process of pumpkin was investigated. The results suggest that the ANN model provides better generalisation of the drying process as compared to the theoretical models. Consequently, the ANN model is able to describe a wider range of drying experiments while the application of theoretical models is limited to specific experimental conditions in most cases. The ANN model is also able to give better results even when the experimental conditions and data set are altered by the addition of new experimental data. Therefore, the ANN model may be considered as a suitable alternative modelling method in describing the drying behaviour of pumpkin. Thus, the artificial neural networks can be successfully applied for the online monitoring and control of industrial drying processes and operations. However, further study is required to ascertain the suitability of ANN in describing the heat and mass transfer process during drying.

## Acknowledgements

The authors are grateful for the financial support received from Universiti Putra Malaysia under the Geran Putra research funding (GP-IPM/9421900).

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