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Full Length Research Paper

Prediction of quality indices during drying of okra pods in a domestic microwave oven using artificial neural network model

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The ability of artificial neural networks to model non linear complex systems such as drying is increasing. The aim of this work is to develop an artificial neural network model, to predict quality indices of okra pods after drying in a domestic microwave oven that could be a tool used to predict some product quality. The optimal artificial neural network model was found to be a 3-6-4 structure with sigmoid transfer function. This optimal model was capable of predicting the total color change (E), browning index, coefficient of rehydration and bulk shrinkage coefficient with R^2 higher than 0.98 during training phase. It was concluded that the artificial neural network model predicted quality indices better than the multiple linear regression model.

Key words: Artificial neural networks, drying, microwave, prediction, okra, multiple linear regression, quality indices.

INTRODUCTION

In Saudi Arabia, okra is considered as an important vegetable crop, for its economical and nutritive values. It is considered as one of the main vegetable crops cultivated in summer season in Saudi Arabia (Al-Harbi et al., 2008). It is a source of protein, vitamins C and A, iron, calcium (Aworh et al., 1980) and dietary fiber (Adom et al., 1996). Its scientific names are *Abelmoschus esculentus* and *Hibiscus esculentus*. In various parts of the world, it is known as okra and in the Middle East, it is called Bamia, Bamya or Bamieh.

Fresh harvested okra has very high moisture content (88-90% wet basis) with safe moisture content for storage (10% wet basis) (Shivhare et al., 2000). Due to its high moisture content, it is subjected to rapid deterioration, resulting in chemical, physical and biological changes. Under these conditions, its shelf life does not increase (Kumar and Prasad, 2010). Because of its sensitivity to storage, most fresh okras are preserved in some form.

Abbreviations: ANN, Artificial neural network; **RMSE,** root mean square error; **MAE,** mean absolute error; **RSS,** root sum squares; **wb,** wet basis; **db**, dry basis; **MLR,** multiple linear regression; **RMSE,** root mean square.

Freshly harvested okra pods can be sliced, dried and grounded into powder for extension of shelf life (Sobukola, 2009). One of the most widely used methods of food preservation is drying which also extends the shelf-life of food. The major aim of drying agricultural products is the reduction of the moisture content to a level which allows safe storage over an extended period (Doymaz, 2007). Moreover, drying of food materials leads to new more easily handled consumed products (Mousavi and Javan, 2009).

Microwave drying is a rapid drying technique that can be useful to specific foods. Increasing concerns over product quality and production costs have motivated the researchers to investigate and the industry to adopt microwave drying technology. The advantages of microwave drying include shorter drying time, improved product quality, and flexibility in producing a wide variety of dried products (Haghi and Amanifard, 2008). Moreover, the drying characteristics and quality of the final products dried by microwave are dependent on drying time and microwave power (Kassem et al., 2010). No papers were found on the prediction of quality indices for okra pods after drying in a domestic microwave oven. The availability of such information is relevant for understanding the effect of drying process on the material quality. Also, considerations of design of storage containers for dried okra pods must be taken to keep dried materials in good case. In drying process of fruits and vegetables, mathematical models could be a good tool for predicting product quality after drying. However, for drying process itself, mathematical models have succeeded in getting the constants values that describes the process. For example, Page (1949) model was successfully used to describe the drying characteristics of a variety of agricultural materials like red chili and okra (Gupta et al., 2002; Doymaz, 2005).

Artificial neural network (ANN) is a non-linear statistical data modeling tool that is usually used to model complex relationships between inputs and outputs. ANN considered the analysis to be an alternative approach for the investigation of non-linear relationships in engineering problems. A more realistic and accurate predictions can be obtained through ANN analyses (Akin and Akba, 2010). ANN was successfully used to describe the drying characteristics of a variety of agricultural materials like jackfruit bulbs and leather, strawberries and grapes (Bala et al., 2005; Menli et al., 2009; Kassem et al., 2010), to predict quality changes during osmo-convective drying of blueberries (Chen et al., 2001), to predict food quality (Ni and Gunasekaran,1998), to model temperature and moisture content in tomato slices undergoing microwave-vacuum drying (Poonnoy et al., 2007a) and to estimate moisture ratio of a mushroom undergoing microwave-vacuum drying (Poonnoy et al., 2007b).

Islam et al. (2003) developed an ANN model for rapid prediction of the drying rates using the Page equation fitted to the drying rate curves. The ANN model is verified to provide accurate interpolation of the drying rates and times within the ranges of parameters investigated. Zhang et al. (2002) reported that ANN could predict six performance indices which are energy consumption, kernel cracking, final moisture content, moisture removal rate, drying intensity, and water mass removal rate during rough rice drying. However, the inputs to the ANN model were rice layer thickness, hot airflow rate, hot-air temperature and drying time. The optimal model was a four-layered back-propagation neural network, with 8 and 5 neurons in the first and the second hidden layers, respectively. The mean relative error varied from 2.0 to 8.3% for six predictions with an average of 4.4%. Erenturk and Erenturk (2007) built a feed-forward ANN to estimate moisture content of dried carrot using different drying conditions. Back propagation algorithm was used in training and testing the network. Results concluded that ANN represented drying characteristics better than mathematical models. Lertworasirikul and Tipsuwan (2008) used a multilayer feed-forward neural network to predict moisture content and water activity of semi-finished cassava crackers from a hot air drying. The neural network model was composed of one hidden layer, three inputs (drying temperature, relative humidity and sample temperature), and two state outputs (moisture content and water activity). The best network was composed of nine hidden nodes and uses a logarithmic sigmoid transfer function in the first layer. The mean squared error and regression coefficient between the predicted and experimental outputs from the best network were 0.0034 and 0.991, respectively. Farkas et al. (2000) applied ANN to an agricultural fixed bed dryer and concluded that ANN could be effective for modeling of the grain-drying process. Hernández-Pérez et al. (2004) developed a predictive model for heat and mass transfer during drying of cassava and mango using ANN. The model takes into account the shrinkage of the products as a function of the moisture content. It can be used for online state estimation and control of the drying process.

One of the most important aspects of drying technology is modeling of the drying processes and the quality indices (Di Scala, 2010). The purpose of modeling is to allow the engineers to choose suitable operating conditions for a given product (Khazaei and Daneshmandi, 2007). Classical mathematical modeling is still the basic tool for the performance prediction of agricultural and industrial dryers (Bala et al., 2005). However, regression analysis for drying mint leaves is able to correlate drying constants k and n with drying air temperature (Kane et al., 2009). Also, regression succeeds to correlate drying airflow rate and temperature as the independent variables and product acceptance as the dependent variable during drying process of banana using microwave (Sousa et al., 2004). Also, shrinkage behavior of dried foods was modeled with simple mathematical models (Senadeera et al., 2005).The bulk shrinkage of the potato cubes was well modeled with the moisture content during hot air drying (Frías et al., 2010). The drying constant of potato during microwave drying was modeled by regression as dependent variable and microwave power, sample diameter and sample thickness were considered as independent variables (Haghi and Amanifard, 2008*)*. The predictions in such studies were excellent, but the different forms of the mathematical models require the formulation of an analytical description (Bala et al., 2005). In contradition, the ANN for modeling does not require the formulation of an analytical description (Bala et al., 2005). The aim of this work is to develop an ANN model to predict quality indices of okra pods during drying in a domestic microwave oven. However, mathematical model which is linear regression equation was used for comparison with the ANN model in order to investigate the appropriate model for predicting quality indices.

MATERIALS AND METHODS

Sample preparation

Green fresh okra pods with similar size, shape and color were obtained from a local market. The pods were sized (3-4 cm). The okra pods were stored in refrigerator at 4–5°C for about one day for equilibration of moisture and then used for drying experiments. The okra samples were blanched in a hot water at temperature 95°C for 5 min and were immediately cooled in a chilled water to avoid over processing (Kumar and Prasad, 2010). The top and tip were separated and the remaining okra pod was used without cut. The electric laboratory oven was used to determine the initial moisture content of the okra samples. The oven was adjusted at 70°C for 24 h (AOAC, 1984). Reported values of the initial moisture content were in three replications. The mean initial moisture content of the okra samples was 89.41 ± 0.4% (wb).

Drying equipment and drying procedure

Drying treatment was performed in a home microwave oven (Moulinex Model PTiMO) with technical features of 220 V and 50 Hz. During drying experiments, sample of 100 g was uniformly spread in a glass dish with diameter of 31 cm and about 1 cm depth in a single layer and placed at the centre of the oven. Some microwave output power levels (75, 150,300, 500,700 or 900 W) were investigated in this study. The drying procedure was done by operating the microwave oven for a cycle of 1 min ON then 5 min OFF for specific microwave power. Moisture loss was periodically measured by taking out the glass dish and weighing on the digital balance with a precision of 0.01 g. Three replications of each experiment were performed according to a preset microwave output power and time schedule, and the data given was an average of these results. The microwave power was applied until the desired final weight of dry okra pods was obtained. However, the desired final weight of dry okra pods was calculated according to Brennand (1994). All weighing processes during drying experiments were completed in less than 10 s. The final drying time and final moisture content corresponding to each power level were recorded and they were considered as affected parameters on quality indices.

Quality indices

Color measurements

The evaluation of the quality of the dried products was based on color, shrinkage and rehydration capacity. However, Reddy (2006) reported that the color and rehydration ratio are very important quality attributes of dehydrated products. Moreover, color is an important quality attribute of foods to most consumers. It is an index of the inherent good quality of foods and the association of color with the acceptability of food is universal. Moreover, drying time affects color change and rehydration ratio during drying process (Akoy et al., 2008).

The color measurement is normally done in an indirect way to estimate the color changes of foods since it is simpler and faster compared to other methods (Maskan, 2001). Hunter Laboratory system is a type of measuring color systems. It has proven valuable in describing visual color deterioration and providing useful information for quality control in various fruits and vegetables during drying such as mango slices (Akoy et al., 2008), kiwifruit slices (Mohammadi et al., 2008) and spinach (Dadali et al., 2007a). The color parameters are expressed as L (lightness), a (redness/greenness) and b (yellowness/blueness). The Hunter "L" value represents the lightness or darkness of a sample on a scale of 0 to 100 (100 being white and 0 being black). Hunter "a" value represents the greenness or redness of the sample (-50 being green and +50 being red). Hunter "b" value is also rated on a scale of -50 to +50, with -50 representing blue and +50 representing yellow.

In this study, the color was measured using a simple digital imaging method (Yam and Papadakis, 2004). A high-resolution digital camera (Canon XUS105, 12.0 MegaPixel, 4 digital zoom) was used to measure color by capturing the color image of the sample under two 40 W florescent light. A laptop computer (Acer T6500, 4.0 GB RAM, 320 GB hard disk) was used. Since the color images of the samples were captured, the color was analyzed quantitatively using Photoshop (Adobe Systems, 2002). The histogram window of Photoshop used to determine the color distributions along the x-axis and y-axis as shown in Figure 1. In Figure 1, the histogram window displays the statistics (mean, standard deviation, median, percentage, and so on) of the color value, lightness, for a selected area in the dried okra image. The histogram window can also display the statistics for two other color values (a and b), which is done by selecting a and b under the channel drop-down menu. Hence, the average color of a dried okra sample or any portion of it can be obtained easily using the histogram window. The lightness, a, and b in the histogram window are not standard color values. However, they can be converted to L*, a* and b* values using the following formulas (Yam and Papadakis, 2004),

$$L* = \frac{Lightness}{255} \cdot 100 \qquad (1)$$

$$a* = \frac{240a}{255} - 120 \qquad (2)$$

$$b* = \frac{240b}{255} - 120 \qquad (3)$$

Where, E indicates the total color change of a sample in comparison to color values of an ideal sample having color values of L*, a* and b*. Fresh okra sample was taken as the ideal sample. The total color change (E) parameter is calculated as follows:

$$E = \left[(L* - L**)^2 + (a* - a**)^2 + (b* - b**)^2 \right]^{0.5} \qquad (4)$$

Where, L* is the lightness of fresh samples; L** is the lightness of dried samples; a* is the redness of fresh samples; a** is the redness of dried samples; b* is the yellowness of fresh samples and b** is the yellowness of dried samples.

Browning index (BI) represents the purity of brown color and is considered as an important parameter associated with browning (Mohammadi et al., 2008). The browning index after drying was calculated as follows (Dadali et al., 2007b):

$$BI = \frac{[100(x - 0.31)]}{0.17} \qquad (5)$$

$$x = \frac{(a^{**} + 1.75L^{**})}{(5.645L^{**} + a^{*} - 3.012b^{**})} \qquad (6)$$

Bulk shrinkage

The drying of a product usually results in a smaller size than the original wet form. A 50 ml graduated cylinder was used to get the

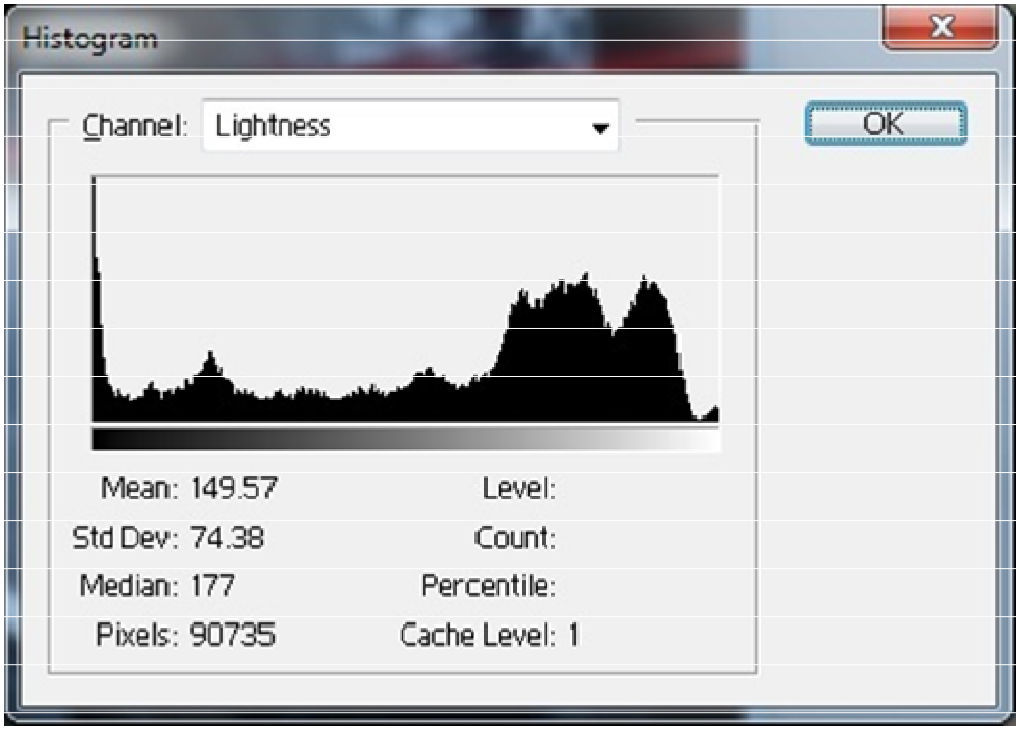

Figure 1. Histogram windows in photoshop.

volume of fresh and dried samples in this study. However, Lazano et al. (1983) described the bulk shrinkage coefficient by:

$$S_b = \frac{V_{b(X)}}{V_{b(0)}} \times 100 \tag{7}$$

Where, S_b is the bulk shrinkage coefficient (%); $V_{b(x)}$ is the bulk volume m^3 at moisture content X and $V_{b(o)}$ is the bulk volume m^3 at initial moisture.

Rehydration capacity

The rehydration properties, rehydration rate, and rehydration capacity are important characteristics of many products, related to their later preparation for consumption (Krokida and Maroulis, 2000). The products with high rehydration capacity are tastier and retain their fresh appearance (Jokić et al., 2009). The rehydration capacity was used as a quality characteristic of the dried product (Velić et al., 2004). Rehydration capacity is useful to determine how the dried product reacts with the moisture because dried okra can be consumed in its rehydrated form. Rehydration is traditionally performed by immersion of the dried fruit in water at ambient temperature. However, this process can take long time and does not guarantee in general, homogeneous distribution of water. To overcome these limits, the achievement of larger rehydration temperature or the use of steam has been proposed (Lewicki, 1998). The rehydration in this study was achieved by boiling 10 g of dried okra in 300 ml distilled water for 30 min (Mohamed et al., 2010). For the rehydration capacity, Venkatachalapaty (1998) used equation 8 for calculating the coefficient of rehydration:

$$COR = \frac{m_{rh}(100 - M_{in})}{m_{dh}(100 - M_{dh})} \tag{8}$$

Where, COR is the coefficient of rehydration; m_{rh} is the mass of rehydrated sample; m_{dh} is the mass of dehydrated sample; M_{in} is the initial moisture content % (wet basis) of the sample before drying and M_{dh} is the moisture content % of the dry sample (wet basis).

Development of ANN model

ANN consists of simple processing elements or 'neurons' linked with each other in a particular configuration. The basic working mechanism of a neuron is shown in Figure 2 where the neuron receives a series of inputs, each carrying a specific synaptic weight. The result is filtered by an activation function that generates an output signal with certain intensity, which serves as the stimulus for the next neuron (Haykin, 1999). Training of the network consists of the adjustment of the weight coefficients of input neuron signals.

There are many types of ANN structures and training algorithm. In many network types, a feed forward neural network with back propagation algorithm is used in agricultural applications such as the study conducted by Ghamari et al. (2010). The basis of feed forward neural network with back propagation algorithm is that the signals coming from the previous layer are processed and then the output is transmitted to the next layer (Özbek and Fidan, 2009). In order to design ANN model, commercial neural network software of QNET 2000 for windows (Vesta Services, 2000) was used. The ANN used in this study was a standard back-propagation neural network with three layers, an input layer, a hidden layer and an output layer. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, which

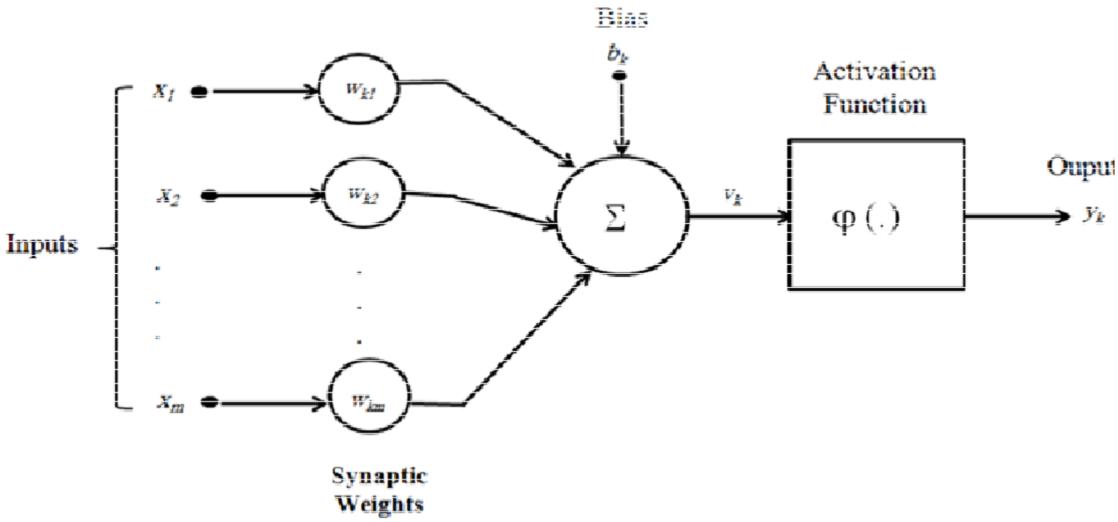

Figure 2. A single neuron model (Haykin, 1999).

Table 1. The randomized raw data used in training and testing the developed ANN model.

Data set	Input variable			Output variable			
	Microwave power (W)	**Final drying time (Min)**	**Final moisture content (%db)**	**Total color change (E)**	**Coefficient of rehydration**	**Bulk shrinkage coefficient (%)**	**Browning index**
Training	500	15	11.31	26.15	0.0416	69.24	20.20
	700	16	11.01	25.65	0.0454	68.11	27.97
	900	14	10.65	31.00	0.0442	57.47	32.25
	300	18	11.11	26.57	0.0363	56.47	18.68
	700	14	10.55	26.47	0.0442	67.14	27.61
	900	13	10.65	31.14	0.0453	56.93	31.95
	300	16	10.87	26.69	0.0370	57.89	18.63
	700	15	10.76	25.51	0.0435	66.98	31.01
	75	18	11.25	27.63	0.0431	63.50	39.40
	150	19	11.25	23.12	0.0343	59.47	21.57
	150	17	10.89	23.02	0.0351	60.22	20.96
	75	19	11.31	27.62	0.0440	63.63	38.27
Testing	75	20	11.43	27.70	0.0440	64.10	40.22
	500	16	11.20	25.82	0.0419	66.98	24.44
	150	18	11.09	23.21	0.0349	60.28	21.12
	300	17	10.98	26.69	0.0368	56.93	18.31
	900	12	10.71	31.12	0.0443	58.44	33.25
	500	17	11.12	25.66	0.0416	68.40	23.65

associates input vectors with specific output vectors. Before training, a certain preprocessing steps on the network inputs and targets to make more efficient neural network training was performed. The range of input and targets values was in the range of 0.15 to 0.85, that is, normalizes the inputs and target values. The randomized raw data used in training and testing the developed ANN model is illustrated in Table 1.

The inputs to the ANN model in this study were final drying time (min), final moisture content (%db) and microwave power (W). The outputs of the ANN were the total color change (E), browning index, coefficient of rehydration and bulk shrinkage coefficient. The randomized data were used in training and the software is ordered to select the testing points. The test points provide an independent measure of how well the network can be expected to perform on data not used to train it. 12 of the data were taken for the training and 6 points for the test set. However, the software picks the test points randomly from the original data. While the testing points was entered to ANN as input, the total color change (E), browning index, coefficient of rehydration and bulk shrinkage coefficient were determined as the output of the ANN.

Table 2. Effects of mean different microwave power, final drying time and final moisture content on the mean of total color change (E), coefficient of rehydration, bulk shrinkage coefficient and browning index.

Input variable			Output variable			
Microwave power (W)	**Final drying time (Min)**	**Final moisture content (%db)**	**Total color change (E)**	**Coefficient of rehydration**	**Bulk shrinkage coefficient (%)**	**Browning index**
75	19	11.33	27.65	0.0437	63.74	39.29
150	18	11.08	23.12	0.0348	59.99	21.22
300	17	10.99	26.65	0.0367	57.10	18.54
500	16	11.21	25.88	0.0417	68.21	22.76
700	15	10.77	25.88	0.0444	67.41	28.86
900	13	10.67	31.09	0.0446	57.61	32.49

Various three layers of ANN structures were investigated, including different number of neurons in the hidden layer, different values of the learning coefficient and the momentum, and different transfer functions. Training a given neural network was achieved; besides, its performance was evaluated using the selected testing points. The best ANN structure and optimum values of network parameters were obtained on the basis of lowest error on training and test sets of data, by trial and error.

Development of multiple linear regression (MLR) model

MLR analysis was performed using the data analysis tool within Microsoft Excel. The MLR analyses was performed from experimental data (Table 1) used in training the ANN model to establish a mathematical relationship for predicting total color change (E), browning index, coefficient of rehydration and bulk shrinkage coefficient (dependent variables) as a function of the three independent variables (microwave power, final drying time and final moisture content). The mathematical relationship has the following form:

$$Y = \beta_0 + \beta_1 \times X1 + \beta_2 \times X2 + \beta_3 \times X3 + \beta_4 \times X1^2 + \beta_5 \times X2^2 + \beta_6 \times X3^2 \tag{9}$$

Where, X_1 is the microwave power (W); X_2 is the final drying time (min) and X_3 is the final moisture content (%, db); Y is the dependent variables [that is, total color change (E, dimensionless), browning index (dimensionless), coefficient of rehydration (dimensionless) and bulk shrinkage coefficient (%)] and β_0 , β_1 , β_2 , β_3 β_4 , β_5 and β_6 are regression coefficients.

Determination of errors in quality indices predictions

The accuracy of ANN and MLR predictions was evaluated using different error statistics as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| QI_{iobs} - QI_{ipre} \right| \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} \left(QI_{i\,obs} \quad QI_{i\,pre}\right)^2}{N}} \tag{11}$$

Where, QI_{iobs} and QI_{ipre} are the observed and predicted quality indices, respectively by different models; N is the number of data points; MAE is the mean absolute error and RMSE is the root mean square. In addition, the coefficient of determination (R^2) was selected to measure the linear correlation between the observed and the predicted values. The optimal correlation coefficient value is unity.

RESULTS AND DISCUSSION

The mean measured color characteristics of the fresh okra pods were L* 47.85, a* -4.28 and b* 23.28. The effects of the mean different microwave power, final drying time and final moisture content on the total color change (E) of the dried okra samples are shown in Table 2.

Generally, the microwave drying process changed color. However, the values of the total color change (E) increased during microwave drying. However, all samples are treated with the same treatment, so these changes may be due to the microwave power effect. Also, the effects of different microwave power, final drying time and final moisture content on browning index of the dried okra samples are shown in Table 2. The high browning index occurred during drying with 75 W microwave power. The shrinkage is presented in this study in terms of the percentage of volume change. The results in Table 2 clearly show less shrinkage when the process was achieved with 300 and 900 W microwave power. Also, the rehydration capacity was calculated in this study through equation 8 in terms of a rehydration coefficient in which higher value correlates with a higher capacity of rehydration. The results in Table 2 clearly show less rehydration coefficient when the process was achieved with 300 and 900 W microwave power.

Prediction of quality indices

Preliminary trails indicated that, one hidden layer network performed better results than other hidden layers. ANN is used to learn and predict the correlation between input

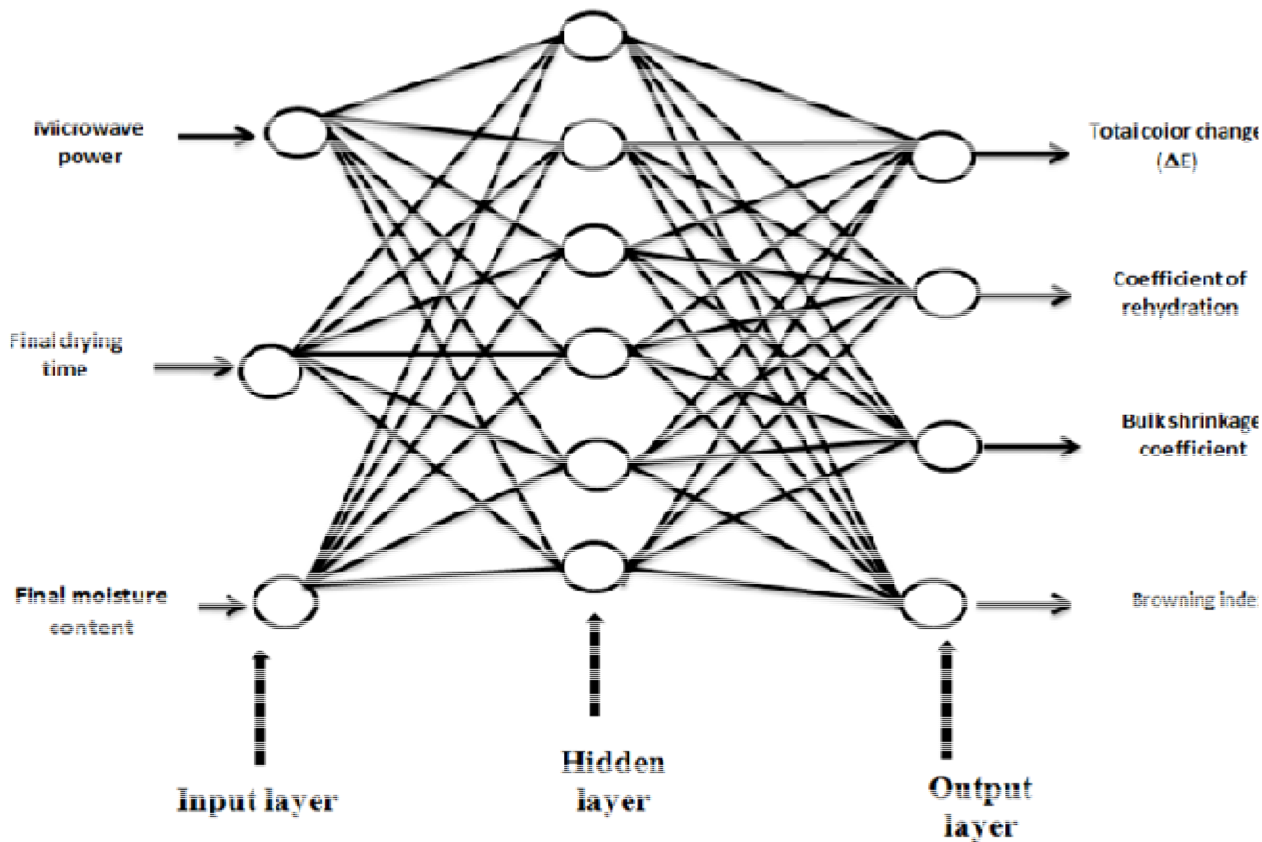

Figure 3. The developed ANN model for predicting the total color change (E), coefficient of rehydration, bulk shrinkage coefficient and browning index of dried okra pods by microwave oven.

and output parameters. To determine the optimal number of neurons in hidden layer, training was used for 3-n1-4 architectures. The number of neurons in the hidden layer (n1) was studied from 1 – 12. Results show that among the various structures, the best training performance to predict quality indices belong to the 3-6-4 structure and Figure 3 illustrated this structure. Meanwhile, root mean square error during training process is shown in Figure 4. Also, the network definition and training control parameters during training and testing phases is shown in Figure 5. Table 3 illustrates network statistics after training and testing phases.

Figure 6 shows the relationships and coefficients of determination between the observed and the predicted values during testing phase using ANN and MLR models for the total color change (E), browning index, coefficient of rehydration and bulk shrinkage coefficient of dried okra pods by microwave oven. The figures clearly show that the points during the testing process, are uniformly scattered around the regression lines with high linear correlations represented by the values of coefficients of determination (R^2) that were 0.883,0.980,0.850 and 0.968 when using ANN model in predicting total color change (E), coefficient of rehydration, bulk shrinkage coefficient and browning index, respectively. Meanwhile, when using MLR in predicting the same quality indices, lower coefficients of determination (R^2) that were 0.696, 0.301, 0.462 and 0.266 for total color change (E), coefficient of rehydration, bulk shrinkage coefficient and browning index, respectively were seen. In Tables 4 and 5, it can be seen that the ANN model was more accurate in predicting the quality indices compared to MLR model as suggested by the statistical measures. In general, however, the RMSE and MAE measured showed a small error between the observed and the predicted values for the quality indices (Tables 4 and 5), suggesting that the employed ANN model was very accurate in predicting the values of the quality indices of okra pods dried in the microwave oven. These results suggest that the model can be used as a reliable tool that can be employed for expected quality indices of okra pods dried in the microwave oven at any values falling within the range of values in this study, of microwave power, final drying time and final moisture content of the pods. Therefore, an operator can select in advance using the model, the combination of microwave power, final drying time and final moisture content that would produce the acceptable quality indices during microwave drying process of okra pods. Table 6 illustrates regression coefficients for

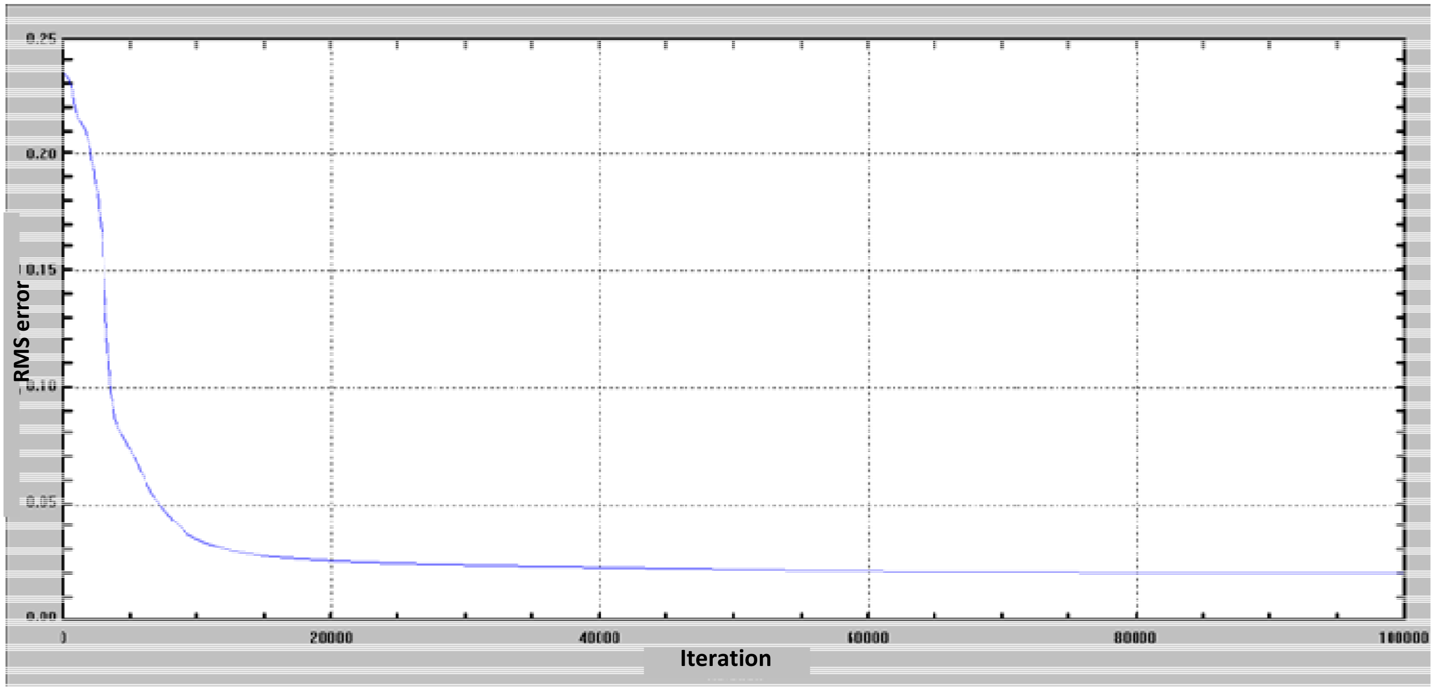

Figure 4. Root mean square error during training process.

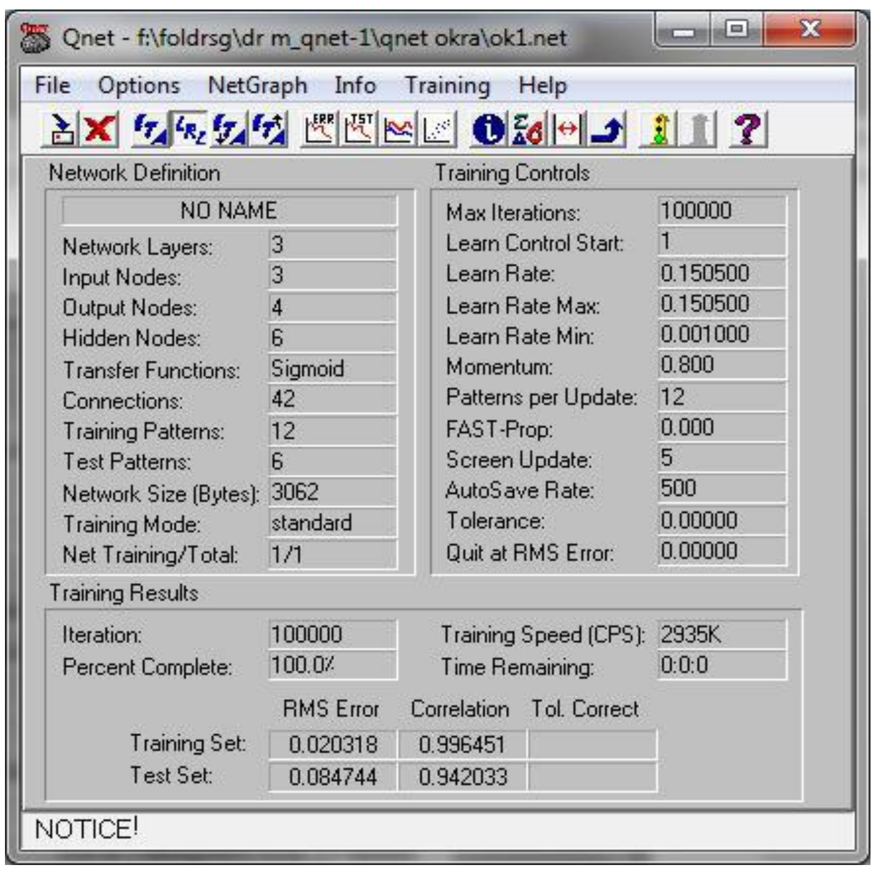

Figure 5. Network definition and training control parameters during traing and testing phases.

Table 3. Network statistics from Qnet software.

Node	Training data			
	Standard deviation	Bias	Maximum error	Correlation
Total color change (E)	0.1401	0.0031	0.3582	0.9983
Coefficient of rehydration	0.0004	-0.000005	0.0010	0.9943
Bulk shrinkage coefficient	0.2187	0.0047	0.4359	0.9989
Browning index	0.7799	-0.0001	2.0609	0.9939
Test data				
Total color change (E)	1.1778	0.7908	2.0232	0.9395
Coefficient of rehydration	0.0011	0.0006	0.0025	0.9898
Bulk shrinkage coefficient	1.8151	-0.7437	4.2103	0.9221
Browning index	1.8226	-1.2192	3.4750	0.9839

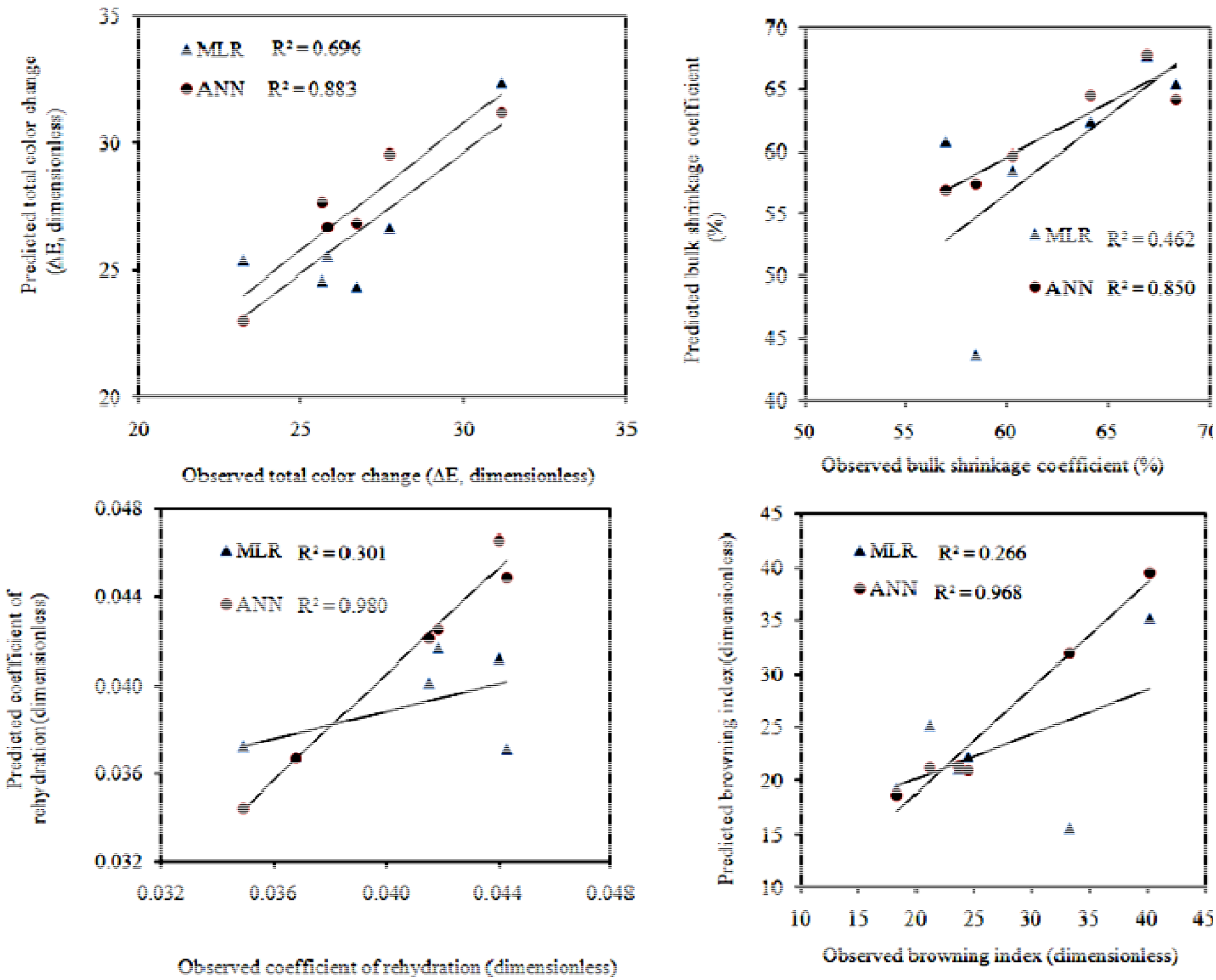

Figure 6. Relationships and coefficients of determination between the observed and the predicted values during testing phase using ANN and MLR models for the total color change (E), browning index, coefficient of rehydration and bulk shrinkage coefficient of dried okra pods by microwave oven.

Table 4. Error criteria during training process of ANN model and building MLR model when predicting quality indices of okra pods dried in microwave oven.

Quality Indice	RMSE		MAE		R^2	
	MLR	ANN	MLR	ANN	MLR	ANN
Total color change (E)	1.425	0.140	1.173	0.076	0.648	0.997
Coefficient of rehydration	0.0023	0.0004	0.002	0.0003	0.688	0.989
Bulk shrinkage coefficient	2.772	0.219	2.274	0.148	0.629	0.998
Browning index	3.900	0.780	3.336	0.418	0.696	0.988

ANN**,** Artificial neural network; RMSE, root mean square error; MAE, mean absolute error; MLR, multiple linear regression.

Table 5. Error criteria during testing process of ANN and MLR models when predicting quality indices of okra pods dried in microwave oven using.

Quality Indice	RMSE		MAE		R^2	
	MLR	ANN	MLR	ANN	MLR	ANN
Total color change (E)	1.533	1.178	1.364	0.855	0.696	0.883
Coefficient of rehydration	0.003	0.001	0.002	0.001	0.301	0.980
Bulk shrinkage coefficient	6.432	1.815	4.295	1.155	0.462	0.850
Browning index	7.815	1.823	5.418	1.386	0.266	0.968

ANN**,** Artificial neural network; RMSE, root mean square error; MAE, mean absolute error; MLR, multiple linear regression.

Table 6. Regression coefficients of equation 9 for predicting quality indices of okra pods dried in microwave oven using MLR.

Regression coefficient	Quality indices			
	Total color change (E)	Coefficient of rehydration	Bulk shrinkage coefficient	Browning index
β_0	34.96	4.644	8002.252	8376.991
β_1	-0.0176	-0.00002	0.014	-0.088
β_2	-2.506	0.0231	39.534	44.219
β_3	0.4291	-0.8799	-1515.434	-1592.772
β_4	0.00002	0.00000004	-0.000005	0.00012
β_5	0.0553	-0.000696	-1.189	-1.299
β_6	0.1223	0.0404	69.388	72.752

equation 9 of quality indices of okra pods dried in microwave oven.

The Qnet algorithm for computing percent contribution considers how the change in each input changes the output prediction. For each case in the training set, each input is varied from minimum to average to maximum. The change in output is computed as the square root of the RSS (root sum squares) for each input node over all cases. The RSS for each input are presented as a percent of the total of all the computed input RSS values (Vesta Services, 2000). The contribution percentage of the three input variables to the outputs was calculated using the developed ANN model and results are illustrated in Table 7. It can be deduced from Table 7 that the major contribution to the quality indices was attributed to the input variable of microwave power with a contribution percentage of 39.32, 51.34, 44.81 and 58.68 for total color change (E), coefficient of rehydration, bulk shrinkage coefficient and browning index, respectively. Hence, the accuracy with which the microwave power rate was adjusted would greatly influence the resulting predicted quality indices within the boundaries of the

Table 7. Contribution percentage of three independent variables used in the 3-6-4 ANN model for quality indices of okra pods dried in microwave oven.

Input variable	Contribution (%)			
	Total color change (E)	**Coefficient of rehydration**	**Bulk shrinkage coefficient**	**Browning index**
Microwave power	39.32	51.34	44.81	58.68
Final drying time	32.57	21.83	31.24	18.26
Final moisture content	28.11	26.83	23.95	23.06

training data set used in this paper. The other variable, that is, final drying time, however, was found to have moderate influence on the predicted quality indices with a contribution percentage of 32.57, 21.82, 31.24 and 18.26 for total color change (E), coefficient of rehydration, bulk shrinkage coefficient and browning index, respectively. Meanwhile, the final moisture content was also found to have moderate influence on the predicted quality indices with a contribution percentage of 28.11, 26.83, 23.95 and 23.06 for total color change (E), coefficient of rehydration, bulk shrinkage coefficient and browning index, respectively.

Conclusion

The results obtained from this study show that the ANN model learned the relationship between the three input factors (microwave power, final drying time and final moisture content) and total color change (E), coefficient of rehydration, bulk shrinkage coefficient and browning index which describe the quality of dried okra pods in domestic microwave as output successfully. ANN model compared to regression model was able to learn the relationship between dependent and independent variables through the data directly without producing a formula. The accuracy of the ANN model is better than regression model. The number of patterns in the training dataset in this research was not very much (12 patterns); nevertheless, the ANN model was able to successfully predict quality indices of dried okra pods in domestic microwave (acceptable values for RMSE, MAE and R^2). If new data for quality indices of dried okra pods in domestic microwave and independent variables are available, the ANN model can easily relearn the relationship between them. The higher performance, higher prediction accuracy, and ability to relearn are important to create a powerful model. Finally, it was found that the prediction performance of ANN model is superior to the regression equation.

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