DE GRUYTER OPEN
Chemical and Process Engineering 2015, 36 (4), 425–436
DOI: 10.1515/cpe-2015-0030
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INVESTIGATION OF INFRARED DRYING BEHAVIOUR OF SPINACH LEAVES USING ANN METHODOLOGY AND DRIED PRODUCT QUALITY

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Effects of infrared power output and sample mass on drying behaviour, colour parameters, ascorbic acid degradation, rehydration characteristics and some sensory scores of spinach leaves were investigated. Within both of the range of the infrared power outputs, 300–500 W, and sample amounts, 15–60 g, moisture content of the leaves was reduced from 6.0 to 0.1±(0.01) kg water/ kg dry base value. It was recorded that drying times of the spinach leaves varied between 3.5–10 min for constant sample amount, and 4–16.5 min for constant power output. Experimental drying data obtained were successfully investigated by using artificial neural network methodology. Some changes were recorded in the quality parameters of the dried leaves, and acceptable sensory scores for the dried leaves were observed in all of the experimental conditions.

Keywords: Artificial neural network (ANN), infrared*,* spinach drying, ascorbic acid, rehydration, colour parameters

1. INTRODUCTION

In recent years, drying processes have been performed in closed systems such as infrared dryers in order to increase the drying efficiency and also to decrease product quality losses. Infrared drying technique can supply higher energy efficiency, shorter drying time and superior product quality compared to conventional drying methods. Strumillo and Kudra (1986) and Lewis (1996) reported that various infrared heat sources could be effectively used for drying of the biomaterials. According to the findings of Sandu (1986) and Chua and Chou (2003), infrared drying is a low-cost drying method that can be easily employed in rural farming areas. Moreover, it has some advantages, such as versatility, simplicity in terms of the equipment required, high rates in heating and drying, easy installation and low capital cost (Fernandes et al., 2004; Kocabiyik and Tezer, 2009).

Some researhers have used infrared application for drying of food materials; Nowak and Lewicki (2004) for apple, Sharma et al. (2005) and Kumar et al. (2006) for onion, Shi et al. (2008) for blueberry, Kocabiyik and Tezer (2009) for carrot, Ruiz-Celma et al. (2009) for grape by-products, and Doymaz (2011) for sweet potato. However, there is no data found in literature on infrared drying of spinach which is one of the most important vegetables since it is popularly used for culinary purposes, and it is eaten raw, dried, boiled or baked into various dishes. It is low in calories and is a good source of vitamin C which is a hydro-soluble vitamin and sensitive to heat, oxygen, light and considered to be highly sensitive to quality losses during drying (Soysal & Soylemez, 2005).

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Since dried fruits and vegetables have long been regarded as alternative fat-free snacks for health-conscious consumers, not only their nutritional changes, but also other changes such as physical and microstructural changes during and also at the end of the drying process are of importance (Devahastin and Niamnuy, 2010).

The objectives of this work were twofold:

- to determine the effects of microwave power output and sample amount on drying behaviour and some quality parameters of the dried products,
- to model the experimental drying data by using artificial neural network (ANN) methodology.

2. MATERIALS AND METHODS

Fresh spinach samples were obtained from a local market in Malatya, Turkey. Before the experimental studies, the samples were washed and stored at 4°C. In order to determine the initial water content of the samples, AOAC method number 950.46 was applied, and a value of 85.71% was recorded.

The drying studies were carried out using an infrared dryer with dimensions of 53´54´57 cm. The drying chamber was equipped with three near infrared heat lamps (GE, 37771 R40 Heat Lamp), each having a power of 250 W. In order to gather the experimental drying data for spinach leaves, power output of the heat lamps was varied within the range of 300–500 W by adjusting the power output values through a dimmer. The material was placed on the drying plate in monolayer at all experimental conditions. On-line measurement of the amount of the weight changes in the samples during the drying process was determined directly from digital balance (Kern, PCB 2500-2) attached to the equipment. Each drying process was applied until the initial moisture ratio was reduced to 0.1 (±0.01) g water/g dry base.

Effect of infrared radiation on the color parameters of the dried samples was determined with a colorimeter (Minolta Chroma, CR-100, Japan). Its display was set to CIE L a b colour coordinates. Ten random readings for each sample on the drying tray were recorded and an average value for each colour parameter with a standard deviation was calculated. The parameter, L has a range of 0–100 and is the measure of the lightness value, the chromaticity coordinate, a measures red and green when positive and negative respectively, on the other hand, chromaticity coordinate, b measures yellow and blue when positive and negative, respectively.

Rehydration experiments were carried out in distilled water at 20, 40, 60 and 80°C using a water bath (Nuve, NB9). Approximately 2 g of the dried sample was soaked into 200 ml distilled water for 5 hours. At the end of the rehydration period, the samples were taken out, drained carefully on a sieve and then weighed. The following calculations were then made for each sample in order to determine rehydration capacity (RC):

$$RC = \frac{\text{Mass of rehydrated sample}}{\text{Mass of dried sample}} \tag{1}$$

The ascorbic acid content was measured in both fresh and dried spinach samples according to the AOAC method number 967.21 based on the oxidation of ascorbic acid by titration with 2.6 dichlorophenol-indophenol solution. The extraction solution used was metaphosphoric acid-acetic acid solution.

Sensory evaluation of the dried products was carried out by 10 trained sensory panelists. Samples were evaluated for liking on the 9 point Hedonic scale, where 1 corresponded to dislike extremely, 5 to neither like nor dislike, and 9 to like extremely.

Statistical analysis was performed by the statistical method of analysis of variance (ANOVA) using SPSS software program for windows (Trial version 15.0) with 95% confidence interval, in order to find the significance differences among the experimental data sets.

3. THEORETICAL APPROACH

In order to determine the moisture ratio (MR) and drying rate (DR) the following equations were used:

$$MR = \frac{M_i}{M_0} \tag{2}$$

$$DR = \frac{M_{t+dt} - M_t}{dt} \tag{3}$$

where M_i is the moisture content at a specific time (kg/kg dry base), M_0 is the initial moisture content (kg/kg dry base), M_t and M_{t+dt} are the moisture content at t and moisture content at $t+dt$ (kg/kg dry base), respectively, and t is drying time (min).

Artificial Neural Network (ANN) is an information processing system that imitates the behaviour of a human brain by emulating the operations and connectivity of biological neurons (Golden, 1996). It performs a human–like reasoning, learns the attitude and stores the relationship of the processes based on a representative data set. The neural networks do not need much of a detailed description or formulation of the underlying process. Therefore, appeal to practicing engineers who tend to rely on their own data (Haykin, 1999). In recent years, ANNs have been successfully *applied to process modelling* (Cakmak and Boyaci, 2011; Ferreira et. al., 2011; Karadurmus et. al., 2012; Khataee et al., 2011; Siripatrawan and Jantawat, 2009; Yuceer, 2010).

For the development of the neural network model the Neural Network Toolbox and MATLAB (The Mathworks Inc., 2009) were used. A MATLAB script was written, which loaded the data file, trained and validated the network and saved the model architecture. The input and output data were normalised and de-normalised before and after the actual application in the network.

To develop an ANN model for the estimation of moisture ratio (*MR*), the available data set was partitioned into a training and a test sets. Seventy percent of the data was used as a training class. The remaining thirty percent was used as the test data. 78 data set out of 111 was used for training, and the remaining for testing. Two methods were tried as a training method. One of them was Levenberg-Marquardt backpropagation, called as *trainlm* code in Matlab, the other was Bayesian regulation backpropagation, called as *trainbr* code in Matlab. The former is often the fastest backpropagation algorithm, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. It minimizes a combination of squared errors and weights, and determines the correct combination in order to produce a network that generalizes well. While the latter is a network training function that updates the values of weight and bias according to Levenberg-Marquardt optimization. In order to randomise the drying data, rand code was used in Matlab. The sequence of numbers produced by *randperm* is determined by the internal settings of the uniform random number generator. These data were recorded at workspace under the Matlab and both training methods have been implemented on training data and test data. It was seen that R-square values for Levenberg-Marquardt method were higher compared to those for Bayesian regulation in the training stages. As a result, the Levenberg-Marquardt method is found to give better results for available data. The performance function was the sum of the squares of the difference between ANN output and experimental analysis results.

A three layer feed-forward neural network was chosen for modelling purposes. The selected network structure is shown in Fig.1. The first layer has three logarithmic sigmoid (Eq. 2) neurons, the second layer has twenty eight logarithmic sigmoid neurons and the last layer has one linear neuron.

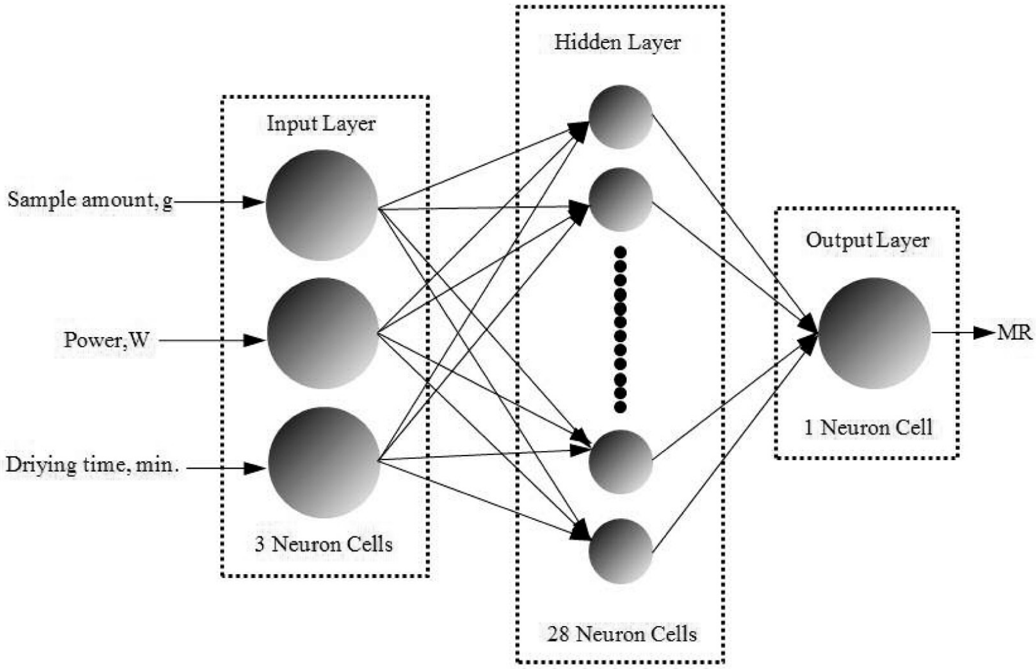

Fig. 1. The selected artificial neural network structure

The transfer functions called logsig in Matlab is given as follows

$$y_i = \frac{1}{1+e^{-z_i}} \tag{4}$$

where z_i is the input of the neuron in hidden layer and y_i is the output of neuron while calculating z_i. Logsig transfer function was calculated for a layer's output from its net input (The Mathworks Inc., 2009).

The performance function was calculated using the mean squared error. The network was trained for a maximum of 5000 epochs. In the course of training, the number of hidden layers, the number of neurons in the hidden layer, training accuracy and number of epochs were determined by trial and error.

After generating sets of training patterns, an appropriate ANN architecture and associated parameters must be chosen for the particular application. The main design parameters are the number of hidden layers, the number of neurons in each layer, and neuron processing functions. The choice of these parameters will depend on the complexity of the system being modelled and they will affect the accuracy of the model. There is no exact guide for the choice of the numbers.

Statistical values such as mean absolute percentage error (MAPE), Root Mean Squared Error (RMSE) and correlation coefficient (R) were determined as follows:

$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|y_i - x_i|}{x_i}\right)\cdot 100 \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}} \tag{6}$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2(y_i - \bar{y})^2}} \tag{7}$$

where x_i is an observed value at the i^{th} time step, y_i is a simulated value at the same moment of time, N is the number of time steps, $\bar{x}$ is the mean value of observations, and $\bar{y}$ is the mean value of simulations.

4. RESULTS AND DISCUSSION

4.1. Drying behaviour

In all cases, the moisture content of the spinach leaves at all experimental conditions was successfully decreased from 6.0 to approximately 0.1 (±0.01) g water/g dry base. Effect of power output and sample amount on the moisture ratio of the leaves was presented in Figs. 2 and 3 respectively. It can be clearly seen that there was a significant decrease in the drying times of the leaves as the infrared power output increased from 300 W to 500 W and the drying process took 3.5–10 min depending on the power level applied. Similar trends were reported by Sharma et al. (2005) for onion, Kocabiyik and Tezer (2009) for carrot and Doymaz (2011) for sweet potato slices. On the other hand, studies carried out to investigate the effect of sample amount on drying times showed an opposite trend, i.e., by keeping the power output constant at 400 W, drying times increased from 4.5 min to 16.5 min as the sample amount increased from 15 g to 60 g.

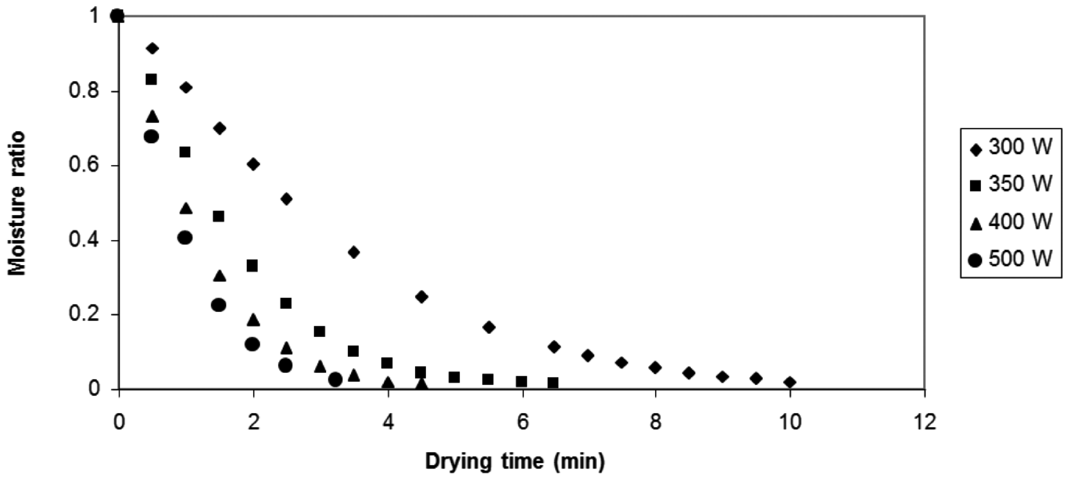

Fig. 2. Effect of infrared drying power output on the moisture ratio of spinach leaves at constant sample amount of 15 g

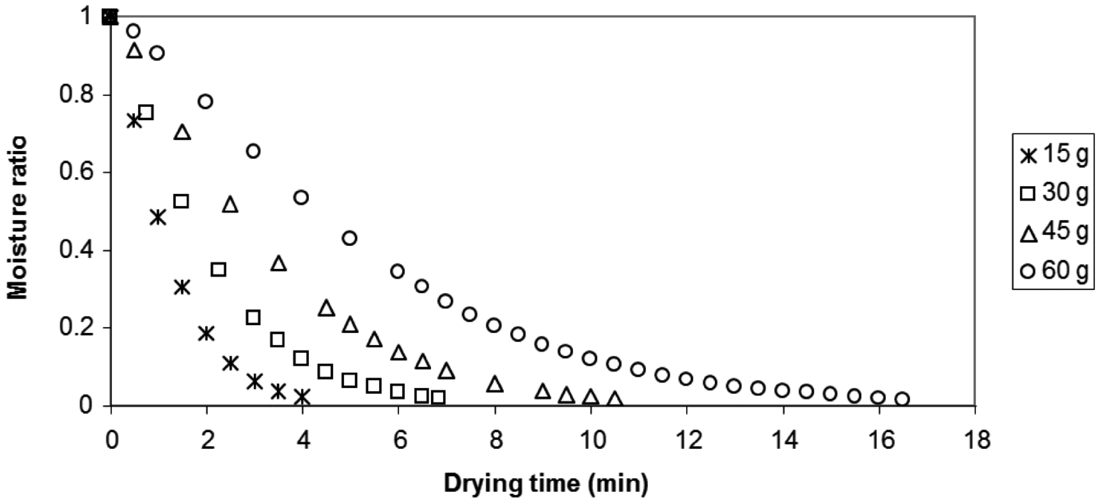

Fig. 3. Effect of sample amount on the moisture ratio of spinach leaves at constant infrared drying power output of 400 W

It can be clearly seen that there was a significant decrease in the drying times of the leaves as the infrared power output increased from 300 W to 500 W and the drying process took 3.5–10 min depending on the power level applied. Similar trends were reported by Sharma et al. (2005) for onion, Kocabiyik and Tezer (2009) for carrot and Doymaz (2011) for sweet potato slices. On the other hand, the studies carried out to investigate the effect of sample amount on drying times showed an opposite trend, i.e., by keeping the power output constant at 400 W, drying times increased from 4.5 min to 16.5 min as the sample amount increased from 15 g to 60 g.

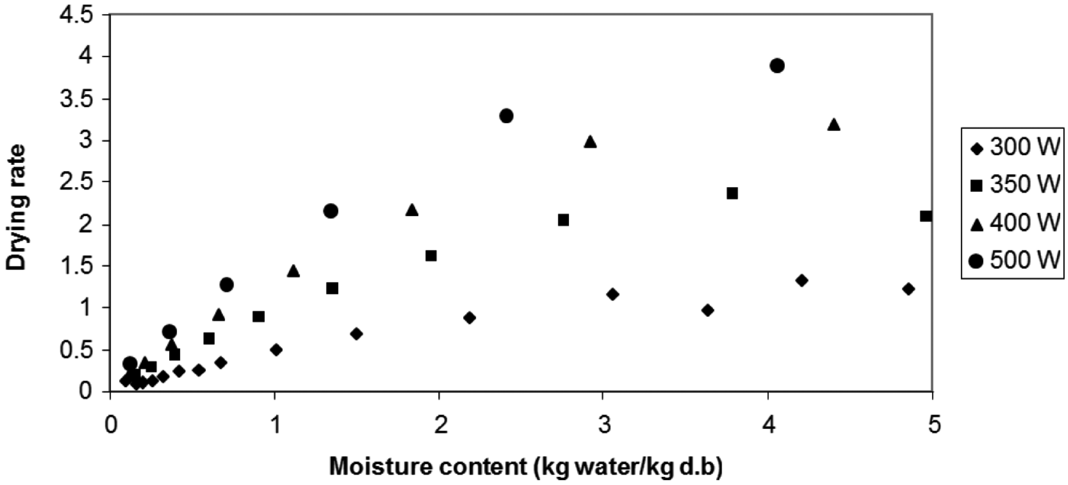

Fig. 4. Effect of drying power output on the drying rate of spinach leaves at constant sample amount of 15 g

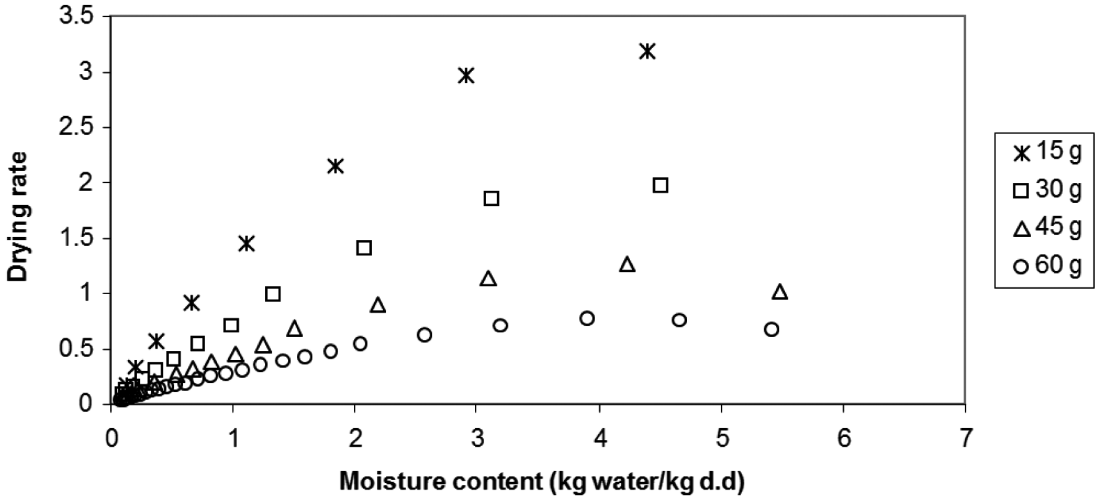

Fig. 5. Effect of sample amount on the drying rate of spinach leaves at constant drying power output of 400 W

The drying rates were calculated from the amount of water removed per unit time and dry base. Therefore, the average drying rates of spinach leaves were within the general of range of 0.274–1.93 kg water/(kg dry base·min) depending on the condition which the drying process was applied. Figs. 4 and 5 show the effect of the infrared power output and sample mass on drying rate as a function of moisture content respectively. As can be seen, drying rate decreased as the infrared power output and moisture content of the samples decreased. At constant power output, increasing the sample amount resulted in decreased drying rates. In all cases constant drying rate period was not observed and therefore the drying process occurred in the falling rate region. Similar trends were recorded by Nowak and Lewicki (2004) for apple, Sharma et al. (2005) and Kumar et al. (2006) for onion, Shi et al. (2008) for blueberry, Kocabiyik and Tezer (2009) for carrot, Ruiz-Celma et al. (2009) for grape by-products, and Doymaz (2011) for sweet potato.

4.2. ANN modeling

The accuracy of ANN models for the learning and the test data were presented in Figs. 6 and 7. As can be seen, a very good agreement between the experimental results and the ANN model was recorded. Besides, the results of the statistical investigations given in Table 1 also support this good agreement.

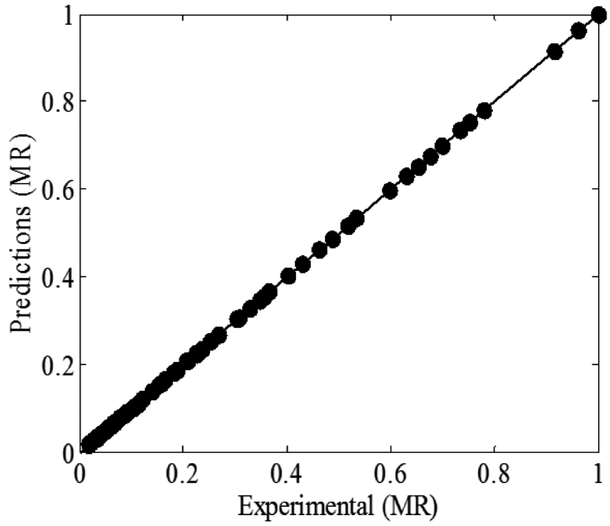

Fig. 6. Comparison of the experimental and the predicted data for the test data

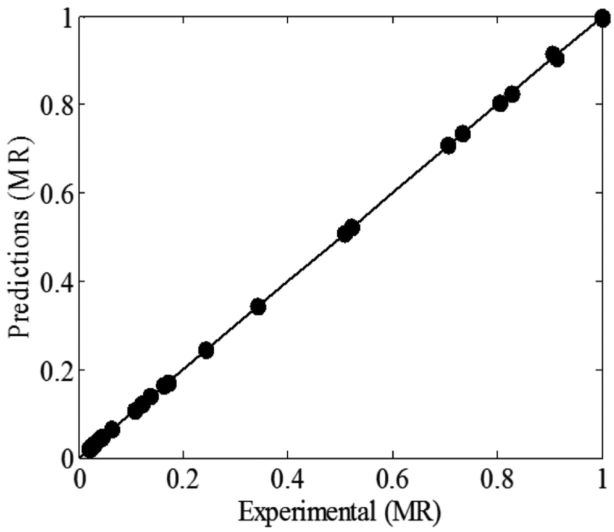

Fig. 7. Comparison of the experimental and the predicted data for the learning data

Table 1. Statistical evaluation of learning and test data

Performance	Training data	Test data
R-square	0.99999	0.99995
MAPE (%)	0.00291	0.95262
RMSE	3.1945×10^{-6}	0.00284

It can be clearly seen from the results that this methodology can accurately predict the drying behaviour of spinach leaves. Of course, many empirical and semi-empirical models available in the literature may be also suitable for this study. However, the superiority of ANN models over these models is not only their accuracy but also their general better performance. ANN models can describe the whole range of experiments while the application of other correlations is only limited to a specific experimental condition. As in the case of this study, the ANN model proposed is able to describe the whole range of experimental conditions very accurately as discussed above.

4.3. Color measurements

Colour change of fruits and vegetables in a drying process is an important parameter as it directly affect consumer acceptance. As reported by Devahastin and Niamnuy (2010), it is the indication of retention of the pigment nutrients e.g., carotenoids, flavonoids, phenols, chlorophyll and betalains of dried fruits and vegetables. It can be clearly seen from the Tables 2 and 3, the values of L and b decreased while those of a increased as the power output and the sample amount increased. Similar trends were observed by Demirhan and Ozbek (2009) for microwave drying of basil.

Table 2. Effect of drying power output on the colour parameters of the spinach leaves of 15 g

Drying power output [W]	L	$-a$	b
Fresh	40 (1.50)*	17.11 (1.22)	19.00 (2.50)
300	38.05 (1.33)	16.50 (0.50)	18.5 (0.80)
350	36 (1.25)	15.45 (0.62)	17.95 (0.74)
400	35.55 (1.05)	15.38 (0.55)	17.52 (0.65)
500	35 (0.89)	14.12 (0.58)	16.95 (0.55)

* Values given in the parenthesis indicate the standard deviations.

Table 3. Effect of sample amount on the colour parameters of the spinach leaves at constant drying power output of 400 W

Sample amount [g]	L	$-a$	b
Fresh	40 (1.50)*	17.11 (1.22)	19 (2.50)
15	35.55 (1.33)	16.38 (0.50)	18 (0.80)
30	34.30 (1.25)	15.40 (0.62)	17.75 (0.74)
45	32.25 (1.05)	14.65 (0.55)	17.3 (0.65)
60	31.10 (0.89)	14.34 (0.58)	16.89 (0.55)

* Values given in the parenthesis indicate the standard deviations.

4.4. Rehydration capacities

Rehydration capacities can be taken as a measure of damage given to the material by drying process (Krokida et al., 1999). Fig. 8 shows that rehydration capacity increased by increasing drying power output and water rehydration temperature, because of less structural damage during rapid drying at high power outputs. However, increasing the sample amount resulted in lower rehydration capacities as can be seen from Fig. 9. This is because of more structural damages occurring during longer exposure times to infrared radiation at high sample amounts as reported by Demirhan and Ozbek (2010) for microwave drying of basil and Sarimeseli (2011) for microwave drying of coriander.

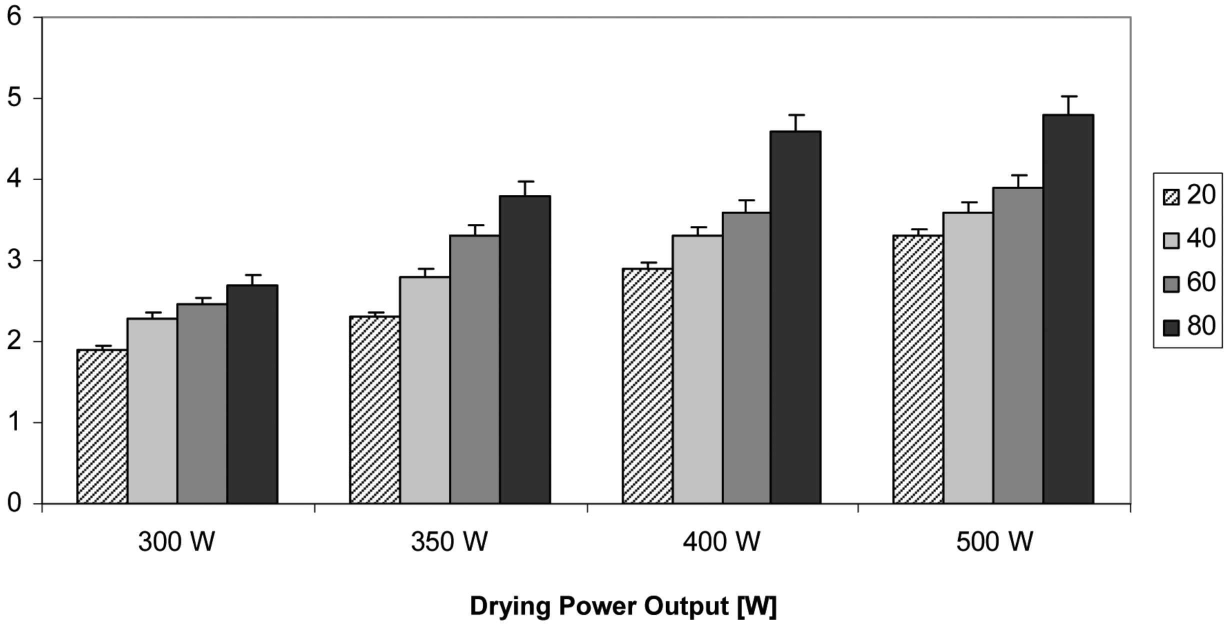

Fig. 8. Effect of drying power output on the rehydration capacities of the spinach leaves of 15 g

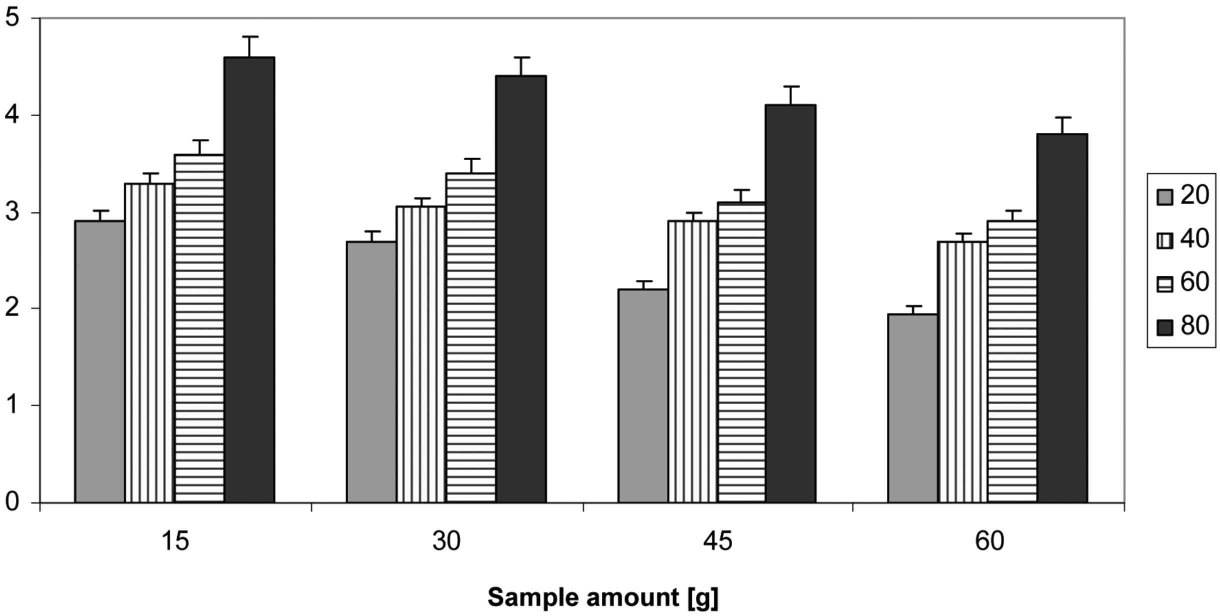

Fig. 9. Effect of sample amount on the rehydration capacities of the spinach leaves at 400 W

4.5. Ascorbic acid degradation

Ascorbic acid is of interest as it is an essential phytochemical found in many fruits and vegetables and exhibits many health benefits. However, ascorbic acid is very susceptible to degradation during drying as mentioned previously (Devahastin and Niamnuy, 2010). It was observed that ascorbic acid degradation increased as the infrared power output increased at constant sample amount as can be seen in Fig. 10. Similar trends were observed by Dadali and Ozbek (2009) for microwave drying of okra and spinach, and Kaya et al. (2010) for hot air drying of kiwifruit. Increasing sample amount also caused vitamin C losses as shown in Fig. 11. This is because longer exposure times needed for higher amount samples result in higher degradation in ascorbic acid content as mentioned previously.

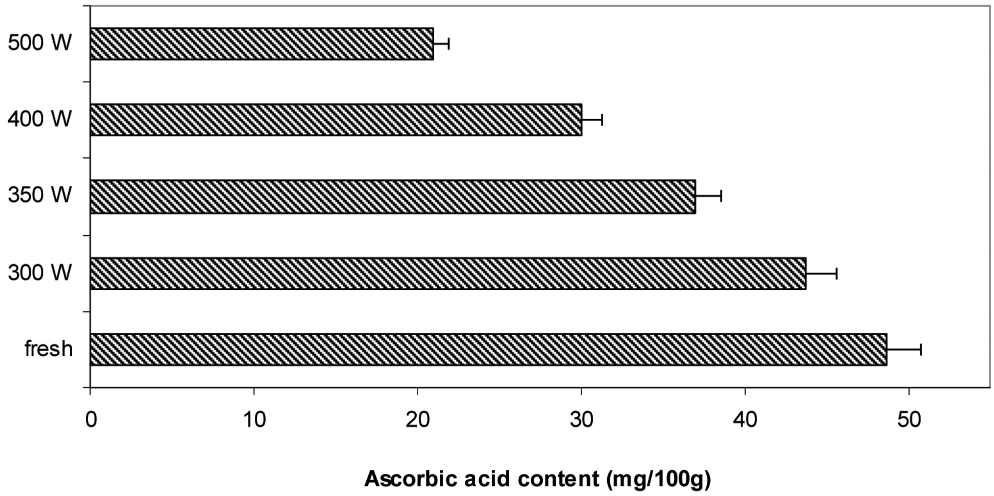

Fig. 10. Effect of drying power output on the ascorbic acid degradation of the spinach leaves of 15 g

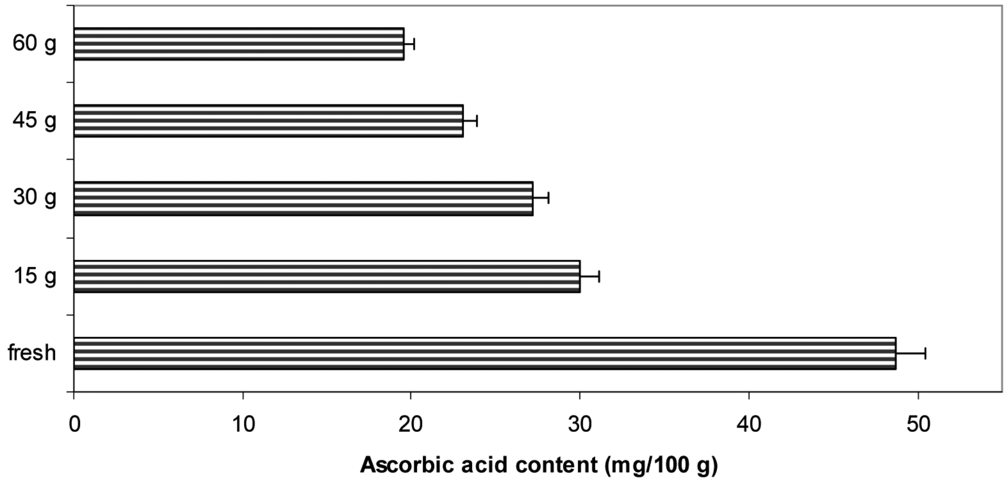

Fig. 11. Effect of sample amount on the ascorbic acid degradation of the spinach leaves at 400 W

4.6. Sensory analysis

Visual appearances of dried fruits and vegetables at the time of sale play a very important role in the quality judgement of consumers. Therefore, analysis including colour, texture and taste can be used in maintenance of product quality throughout the whole processing (Sarimeseli et al., 2014). Visual appearance, texture, flavour and colour evaluation of spinach leaves following infrared radiation were quite acceptable since they received scores above 5 out of 9. Both Table 4 and Table 5 show that no significant differences were found among the data recorded at various drying infrared power outputs.

Table 4. Effect of infrared drying power output on the sensory scores of the spinach leaves at constant sample amount

Drying power output [W]	Visual appearance	Texture	Flavour	Colour	Overall acceptance
250	7.15±0.50	7.23±1.58	6.80±1.10	7.10±0.98	7.00±1.15
300	6.98±0.98	6.99±0.95	6.90±0.95	7.05±1.20	6.95±1.23
350	6.51±1.10	7.11±1.20	7.05±1.37	6.75±1.70	6.90±1.20
400	6.48±0.75	7.02±1.23	7.17±0.99	6.90±1.10	6.80±1.52

Table 5. Effect of sample amount on the sensory scores of the spinach leaves at 400 W

Sample amount [g]	Visual appearance	Texture	Flavour	Colour	Overall acceptance
15	6.51±1.10	7.11±1.20	7.05±0.87	6.75±1.73	6.80±1.20
30	6.80±0.99	7.00±1.25	6.08±1.17	7.11±1.22	7.10±1.20
45	6.95±1.53	6.75±1.12	6.35±1.33	7.04±2.05	6.99±1.50
60	6.65±1.15	6.53±1.82	6.29±1.01	6.88±1.81	6.89±0.92

5. CONCLUSIONS

In the present work, modelling infrared drying behaviour of spinach leaves with ANN methodology, and determining some quality parameters were carried out. The moisture ratios and drying rates were significantly influenced by the infrared power output and the sample amount. Increasing the infrared power output from 300 W to 500 W decreased the drying time from 10 min to 3.5 min, while increasing the sample amount increased the drying time from 4 to 16.5 min. The whole drying process of the spinach leaves occurred in the falling rate period. The experimental results obtained were successfully modelled with artificial neural network methodology which has great advantage of generality over the drying models suggested in literature. Both drying power outputs and sample amount affected the quality parameters, whereas the sensory scores were somewhat similar at all conditions. The values of L and b decreased while those of a increased as the power output and the sample amount increased. Rehydration capacity increased by increasing drying power output and water rehydration temperature, whereas, increasing the sample amount resulted in lower rehydration capacities. Vitamin C losses increased with increasing sample amount and power output values.

REFERENCES

AOAC, 1990. *Official Methods of Analysis*. Association of Official Analytical Chemists, Washington DC.

Boeri C., da Silva F.N., Ferreira S.J., Saraiva J., Salvador A., 2011. Predicting the drying kinetics of salted codfish (*Gadus Morhua*): Semi-empirical, diffusive and neural network models. *Int. J. Food Sci. Technol.,* 46, 509–515. DOI: 10.1111/j.1365-2621.2010.02513.x.

Cakmak Y.S., Boyaci I.H., 2011. Quality evaluation of chickpeas using an artificial neural network integrated computer vision system. *Int. J. Food Sci. Technol.*, 46, 194–200. DOI: 10.1111/j.1365-2621.2010.02482.x.

Chua K.J., Chou S.K., 2003. Low-cost drying methods for developing countries. *Trends Food Sci. Technol.,* 14, 519–528. DOI:10.1016/j.tifs.2003.07.003.

Dadali G., Ozbek, B., 2009. Kinetic thermal degradation of vitamin C during microwave drying of okra and spinach. *Int. J. Food Sci. Nutr.*, 60, 21–31. DOI: 10.1080/09637480701568038.

Demirhan E., Ozbek B. 2009. Color change kinetics of microwave-dried basil. *Drying Technol.,* 27, 156–166. DOI:10.1080/07373930802566101.

Demirhan E., Ozbek B., 2010. Rehydration kinetics of microwave-dried basil. J. Food Process. Preserv., 34, 664–680. DOI: 10.1111/j.1745-4549.2009.00384.x.

Devahastin S., Niamnuy C., 2010. Modelling quality changes of fruits and vegetables during drying: A review. *Int. J. Food Sci. Technol.,* 45, 1755–1767. DOI: 10.1111/j.1365-2621.2010.02352.x.

Doymaz I., 2012. Infrared drying of sweet potato (*Ipomoea Batatas* L.) slices. *J. Food Sci. Technol.*, 49, 760–766. DOI: 10.1007/S13197-010-0217-8.

Fernandes F.A.N., Rodrigues S., Law C.L., Mujumdar A.S., 2011. Drying of exotic tropical fruits: A comprehensive review. *Food Bioprocess Technol.*, 4, 163–185. DOI: 10.1007/s11947-010-0323-2.

Golden R.M., 1999. *Mathematical methods for neural network analysis and design*. MIT Press Cambridge, MA.

Haykin S., 1999. *Neural networks: A comprehensive foundation*. Prentice Hall Inc., USA.

Karadurmus E., Cesmeci M., Yuceer M., Berber R., 2012. An Artificial Neural Network model for the effects of chicken manure on ground water. *Appl. Soft Comput*., 12, 494–497. DOI: 10.1016/j.asoc.2011.08.017.

Kaya A., Aydin O., Kolayli S., 2010. Effect of different drying conditions on the vitamin C (ascorbic acid) content of Hayward kiwifruits (*Actinidia Deliciosa Planch*). *Food Bioprod. Process.,* 88, 165–173. DOI: 10.1016/j.fbp.2008.12.001.

Khataee A.R., Dehghan G., Zarei M., Ebadi E., Pourhassan M., 2011. Neural network modeling of biotreatment of triphenylmethane dye solution by a green macroalgae. *Chem. Eng. Res. Des.*, 89, 172–178. DOI: 10.1016/j.cherd.2010.05.009.

Kocabiyik H., Tezer D., 2009. Drying of carrot slices using infrared radiation. *Int. J. Food Sci. Technol.*, 44, 953–959. DOI: 10.1111/j.1365-2621.2008.01767.x.

Krokida M.K., Maroulis Z.B., 1999. Effect of microwave drying on some quality properties of dehydrated products. *Drying Technol.*, 17, 449–466. DOI: 10.1080/07373939908917545.

Kumar D.G.P., Hebbar H.U., Ramesh M.N., 2006. Suitability of thin layer models for infrared-hot air-drying of onion slices. *LWT Food Sci. Technol.,* 39*,* 700–705. DOI: 10.1016/j.lwt.2005.03.021.

Lewis M.J., 1996. *Physical Properties of Food and Food Processing Systems*. Cambridge: Woodhead Publishing Limited, 277–291.

Nowak D., Lewicki P.P., 2004. Infrared drying of apple slices. *Innovative Food Sci. Emerg. Technol.,* 5, 353–360. DOI: 10.1016/j.ifset.2004.03.003.

Ruiz Celma A., López-Rodríguez F., Cuadros Blázquez F., 2009. Experimental modelling of infrared of drying of industrial grape by-products. *Food Bioprod. Process.,* 87*,* 247–253. DOI: 10.1016/j.fbp.2008.10.005.

Sandu C., 1986. Infrared radiative drying in food engineering: A process analysis. *Biotechnol. Progr.,* 2, 109–119. DOI: 10.1002/btpr.5420020305.

Sarimeseli A., 2011. Microwave drying characteristics of coriander (*Corianderum Sativum* L.) leaves. *Energy Convers. Manage.*, 52*,* 1449–1453. DOI: 10.1016/j.enconman.2010.10.007.

Sarimeseli A., Coskun M.A., Yuceer M., 2014. Modeling microwave drying kinetics of thyme (*Thymus Vulgaris* L.) leaves using ANN methodology and dried product quality. *J. Food Process. Preserv.*, 38, 558–564. DOI: 10.1111/jfpp.12003.

Sharma G.P., Verma R.C., Pathare P.B., 2005. Thin-layer infrared radiation drying of onion slices. *J. Food Eng.,* 67, 361–366. DOI: 10.1016/j.jfoodeng.2004.05.002.

Shi J., Pan Z., Mchugh T.H., Wood D., Hirschberg E., Olson D,. 2008. Drying and quality characteristics of fresh and sugar-infused blueberries dries with infrared radiation heating. *LWT Food Sci. Technol.,* 41, 1962–1972. DOI: 10.1016/j.lwt.2008.01.003.

Siripatrawan U., Jantawat P., 2009. Artificial Neural Network approach to simultaneously predict shelf life of two varieties of packaged rice snacks. *Int. J. Food Sci. Tech.*, 44, 42–49. DOI: 10.1111/j.1365-2621.2007.01631.x.

Soysal Y., Soylemez Z., 2005. Kinetics and inactivation of carrot peroxides by heat treatment. *J. Food Eng.,* 68, 349–356. DOI: 10.1016/j.jfoodeng.2004.06.009.

Strumillo C., Kudra F.T., 1986. *Drying: Principles, applications and design*. New York, NY, Gordon and Breach Science Publishers.

Yuceer M., 2010. Artificial *Neural* Network models for *HFCS* isomerization process. *Neural Comput. Appl.*, 19*,* 979–986. DOI: 10.1007/s00521-010-0437-x.

Received 17 July 2013
Received in revised form 15 July 2015
Accepted 08 October 2015