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Estimation of papaw (*Carica papaw* L.) moisture content using adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithm-artificial neural network (GA-ANN)

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Abstract

Adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithm-artificial neural network (GA-ANN) were used for modeling of the hot-air drying kinetics of papaw slices. The ANFIS and GA-ANN were fed with 3 inputs of drying time (0-320 min), drying temperature (40, 50 and 60 °C) and slice thickness (3, 5 and 7 mm) for prediction of moisture ratio (MR). The triangular membership functions (MFs) were applied and 27 rules were provided for the ANFIS designing. The developed ANFIS predictions were relatively similar to the experimental data (R^2 = 0.9967 and $RMSE$ = 0.0161). The optimized GA-ANN, which included 7 hidden neurons, predicted the MR with a good precision (R^2 = 0.9936 and $RMSE$ = 0.0220). The effective diffusivity for papaw slices was within the range of 6.93×10^{-10} to 1.50×10^{-9} m^2/s over the temperature range. The activation energy was found to be 32.5 kJ/mol indicating the effect of temperature on diffusivity.

Keywords: ANFIS; GA-ANN; Modeling; Papaw

Introduction

Papaw (*Carica papaw* L.), known as an important fruit crop is grown widely in tropical and subtropical regions. This fruit is nutrient and rich in vitamins A and C, and has good organoleptic characteristics as well (Fernandes *et al.*, 2006). According to the report of FAO, papaw has been ranked third with 11.2 million tons or 15.36 percent of the total tropical fruit production in 2010.

Water, as one of the major food components, has a decisive directly influence on the quality and durability of food materials via its impact on many physico-chemical and biological changes (Lenart, 1996). Drying due to the water removal or making water hard to access for microbe development is one of effective operations to reduce the spoilage of agricultural products (Izadifar and Mowla, 2003).

In characterizing the drying parameters, the thin-layer drying procedure was found to be the most feasible tool (Aghdam *et al.*, 2015; Yousefi *et al.*, 2013a). Several models have been used by several authors to estimate the moisture content/drying rate of materials which eventually led to different expression for the prediction of moisture content/drying rate (Yousefi *et al.*, 2013a; Yousefi *et al.*, 2013b). Most of these models are mathematical models which classified to theoretical, semi-theoretical and empirical ones (Demirtas *et al.*, 1998; Midilli *et al.*, 2002). Nowadays, researchers have asserted on the potential of artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS). These techniques can be used as good substitutions for conventional modeling ones such as multiple regression analysis and response surface methodology. Artificial intelligent method has been developed and is extensively used for simulation of drying of agricultural and food materials (Tripathy and Kumar, 2009). Erenturk *et al.* (2004) studied the thin-layer drying of *Echinacea Angustifolia* root. According to their report, the comparison between the obtained R^2 and $RMSE$ values for neural network and regression models revealed that neural network was better than the all mathematical models for predicting the moisture content of the samples. Bala *et al.*

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(2005) modelled drying kinetic of jackfruit in a solar dryer using neural network model. It was reported that a suitable trained model could predict the drying process of jackfruit. Comparison of two modeling methods of mathematical and ANNs to estimate moisture content of papaya fruit slices during hot air drying has been studied (Yousefi *et al*., 2013a). The results showed that estimation of moisture content of papaya fruit could be better modeled by a neural network (R^2 = 0.9994 and *RMSE* = 0.0070) than by the mathematical models (R^2 = 0.9974 and *RMSE* = 0.0123). Prakash and Kumar (2014) generated an ANFIS model to predict the jaggery temperature, the greenhouse air temperature and the moisture evaporation for drying of jaggery inside the greenhouse for natural convection mode. Their results demonstrated that the analytical and experimental results for jaggery drying are in good agreement (R^2 = 0.999-1.00). Tao *et al.* (2016) utilize an ANFIS model to estimate the physicochemical and microbiological parameters of partially dried cherry tomatoes during storage. For all the ANFIS models used, the R^2 values were higher than 0.86 and showed better performance for prediction.

Based on the literature review, no research study has been done on modeling of hot-air drying of papaw using ANFIS and genetic algorithm-artificial neural network (GA-ANN). Therefore, the purpose of this work was to investigate the thin-layer drying process of papaw slices during hot-air drying and modeling of the experimental data using ANFIS and GA-ANN to estimate the moisture content of papaw fruit.

Material and methods

Experimental Study

Papaw fruits were purchased from a local market in the Bahookalat region (Sistan & Baluchestan province, Iran) and stored in a refrigerator at 4 ± 1 °C before they were subjected to the drying process. The fruits were washed, peeled and cut into 3, 5 and 7 mm thick slices. A cabinet dryer (Model JE10 TECH, F-02G, South Korea) with controllable airflow, temperature and air humidity monitoring systems was used for the hot air drying process. The absolute humidity and the hot-air flow ratio for all drying temperatures were 0.6 ± 0.02 g kg^{-1} dry air and 1± 0.1 ms^{-1}, respectively. The initial moisture content was measured using a laboratory oven dryer (Galenkamp, UK) operated at 105 °C. Initial moisture content of the slices was 84.48% ± 0.05% (w. b.). The weight of the samples was recorded by programmable balance software at 5-min intervals until the moisture of the samples reached 5 ± 0.02% (w. b.) in the final product. Drying was carried out at three temperature levels (40, 50 and 60 °C). Moisture ratio (MR) variations with time were plotted for various conditions. MR is defined by the equation (1):

$$MR = \frac{M - M_e}{M_0 - M_e} \qquad (1)$$

Where M is the moisture content of the samples at any drying time and M_0 is the initial moisture content. The moisture ratio equation was simplified to M/M_0 as value of M_e (equilibrium moisture content) is relatively small compared with that of M or M_0 (Akgun and Doymaz, 2005).

ANFIS model

Fuzzy inference systems (FISs) and ANNs can be combined into an integrated system named ANFIS; the integrated system has the advantages of both ANNs (e.g., learning abilities, optimization abilities, and connectionist structure) and FISs (e.g., human like if–then rules, and ease of incorporating expert knowledge available in linguistic terms) (Yolmeh *et al*., 2014).

In ANFIS technique, the neural network learning functions are used for refining each part of the fuzzy knowledge separately. One method for the derivation of a fuzzy rule base is to use the self learning features of artificial neural networks, to define the membership function (MF) based on input– output data. In this study, a hybrid training method (the combination of least-squares and back propagation algorithms) was applied as the training method of the ANFIS.

ANFIS modeling was launched by providing a data set of input-output data points. The data order was the first randomized and then all data were divided into three partitions: 60, 10 and 30% of total data were used for training, validating and testing the network, respectively. Each input-output pair contained three inputs (drying time, drying temperature and thickness) and one output (moisture ratio). It should be noted that the number of MFs applied for each input variable was chosen by trial and errors. The results were obtained using ANFIS toolbox of MATLAB 8.1 (reference the software provider).

GA-ANN model

In brief, the artificial neural network (ANN) is a renowned tool for solving complex, non-linear biological systems and it can give logical results even in complicated cases or in the event of technological faults (Yousefi *et al.*, 2013a). The most popular ANN is the back-propagation feed forward type, whose architecture is based on an input layer comprising all the input variables that feed the network, an output layer which comprises the response of ANN to the desired problem, and hidden layers which are placed between the two layers. The number of input neurons corresponds to the number of input variables into the neural network, and the number of output neurons is the same as the number of target output variables. The number of neurons in the hidden layer depends on the application of the network (Liu and Baughman, 1995). The optimum number of neurons in hidden layer is usually performed by trial and error method. The number of neurons which are respectively placed in the input, hidden and output layers, named topology. The performance of an ANN network is strongly affected by the topology used.

Genetic algorithm (GA) is an optimization technique which can be used for training ANN to overcome inherent limitations of back-propagation (BP). Genetic algorithm can be used in two different ways for training neural networks: (a) Weights optimization and (b) structure and topology optimization (Irani and Nasimi, 2011). The methodology utilized in this work was a hybrid genetic algorithm–neural network strategy. In learning process, weights and biases of neural network were optimized.

The hyperbolic tangent activation functions f (x) (Eq. (2)) were used as the transfer function in the hidden and output layers, because lower normalized mean square error values were obtained for that comparing to sigmoid activation and linear functions.

$$f(x)=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \qquad (2)$$

The output neurons of the hidden and last layers are calculated by Eqs. (3) and (4) as follows:

$$X_j = f(\sum_{i=1}^{n} x_i w_{ji} + w_{j0}) \qquad (3)$$

$$\hat{\psi}_{nl} = f(\sum_{j=1}^{n} X_j w_{kj} + w_{k0}) \qquad (4)$$

where x_i is a variable input, w_{ji} is connection weight between hidden and input neurons, w_{kj} is connection weight between output and hidden neurons, w_{j0} and w_{k0} are biases for the j^{th} and k^{th} neuron, respectively, i is the number of neurons for input and j is the number of neurons for the hidden layer, and k is the number of output neurons. Output of the network, $\hat{\psi}_{nl}$, was compared with the desired output, ψ_{nl}, in the training phase (training by GA), and the error in the form of mean square error (MSE) was calculated for all data. The MSE was obtained from the following equation:

$$MSE=\frac{1}{h}\sum_{p=1}^{h}[(\psi_{nl})_p-(\hat{\psi}_{nl})_p]^{0.5} \qquad (5)$$

Where h is the number of data in the training phase. The goal was to reduce the amount of errors.

In this work, the collected data from the experiments were randomly divided into three partitions consisting training (60%), validation

(10%) and test (30%). To estimate the performance of the trained network, the testing data were compared with the data obtained by the network. The probabilities of the crossover and mutation operators were adjusted at 0.9 and 0.01, respectively.

Besides, a sensitivity analysis was carried out to provide a measure of the relative importance among the inputs of the neural network model and to indicate how the model output varied in response to variation of an input (Bahramparvar *et al.*, 2014). In this research, the NeuroSolution software (version 5.0, NeuroDimension, Inc., USA) was used to design the GA-ANN model.

Results and discussion

The amounts of MR of papaw slices obtained at different drying times for the three thicknesses and three temperatures experimented are depicted in Fig. 1 and Fig. 2, respectively.

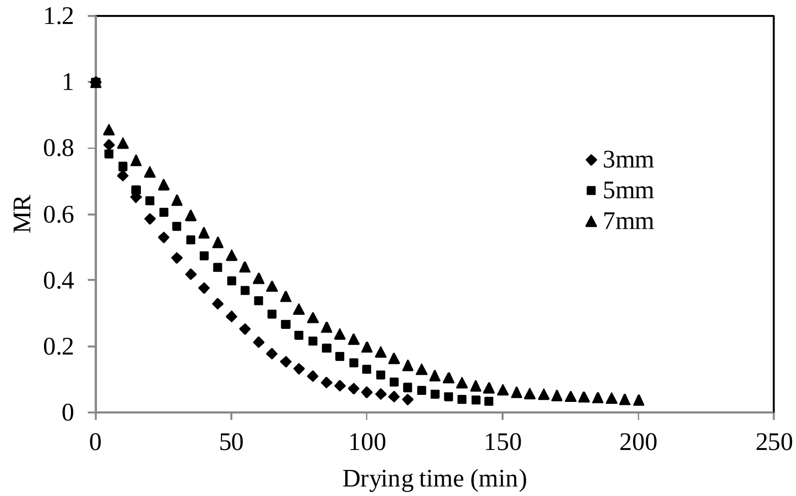

Fig. 1. The influence of papaw slices thickness on moisture ratio (MR) at 60 °C.

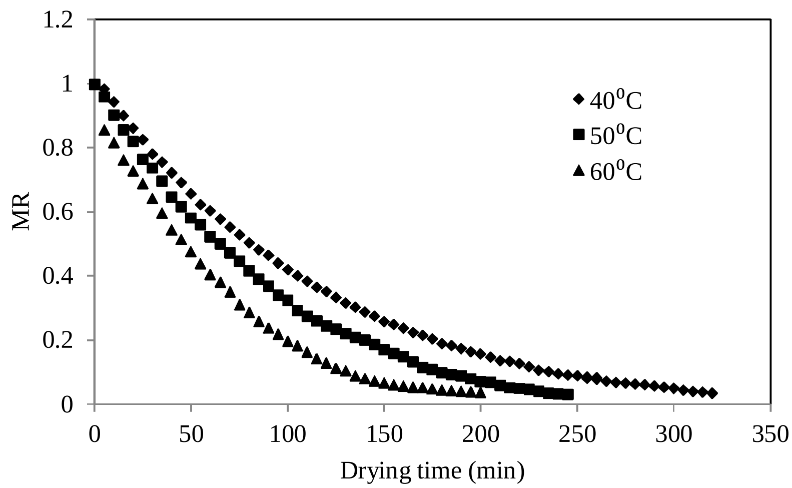

Fig. 2. The influence of drying temperatures on moisture ratio (MR) for the slices with thickness of 7 mm.

As it can be seen, the drying duration at drying temperature of 60 °C was increased (from 115 to 200 min) with increasing thickness from 3 to 7 mm. Similar results have been reported for sweet potato (Diamante and Munro, 1991) and tomato slices (Sadin *et al.*, 2014).The air temperature also had a direct effect on drying rate. As the air temperature increased from 40 to 60 °C for the slices with 7 mm, the drying duration was reduced (from 320 to 200 min). The results of statistical analysis by factorial test proved that drying time (5, 50, 100 and 150 min), temperature (40, 50 and 60 °C) and slices thickness (3, 5 and 7mm) selected in this study had significant effects on moisture content ($p < 0.05$). At higher temperatures, due to the quick removal of moisture, the drying process occurred in a shorter period. The decrease in drying time with increase in drying temperature may be due to increase in water vapor pressure within the papaw slices, which enhances the migration of moisture. Similar observation was reported for apple purees (Vergara *et al*., 1997). The moisture ratio of papaw reduced exponentially as the drying time increased. Continuous decrease in moisture ratio indicates that diffusion governed the internal mass transfer (Haghi and Amanifard, 2008).

ANFIS

The ANFIS network parameters such as the type and number of MF and epochs, have been changed to obtain the best results in terms of model validation. Fig. 3 shows the ANFIS architecture used in the study. The final ANFIS architecture for estimating the MR, with three triangular type MFs for each input (3 inputs) and linear MF for output, and constructed 27 rules resulted high accurate estimation.

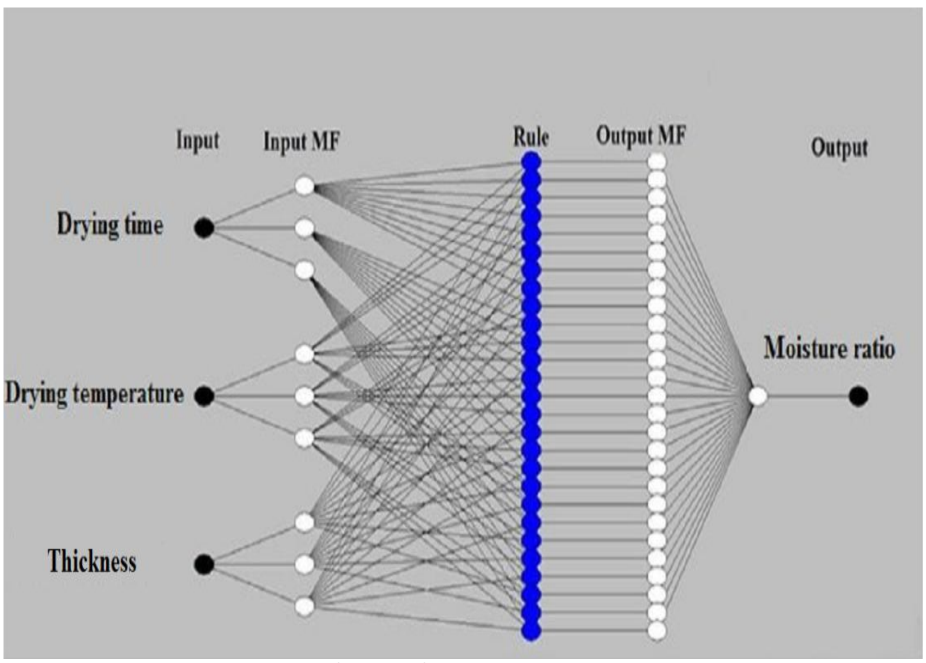

Fig. 3. The general structure of ANFIS for moisture ratio (MR) model with 3 inputs.

As it can be seen in Fig. 4(a), the network is trained well, because the output data are completely near to the train ones and also the training error is low (0.0053) (Fig. 4(b)). Moreover, it was observed that the number of epochs had not a significant influence on the error calculated. Fig. 5 shows the experimental MR values against ANFIS predictions for test data (unseen data) points. As it can be seen, the system was completely efficient to estimate the values of MR obtained in all conditions experimented (R^2 = 0.9967 and $RMSE$ = 0.0161).

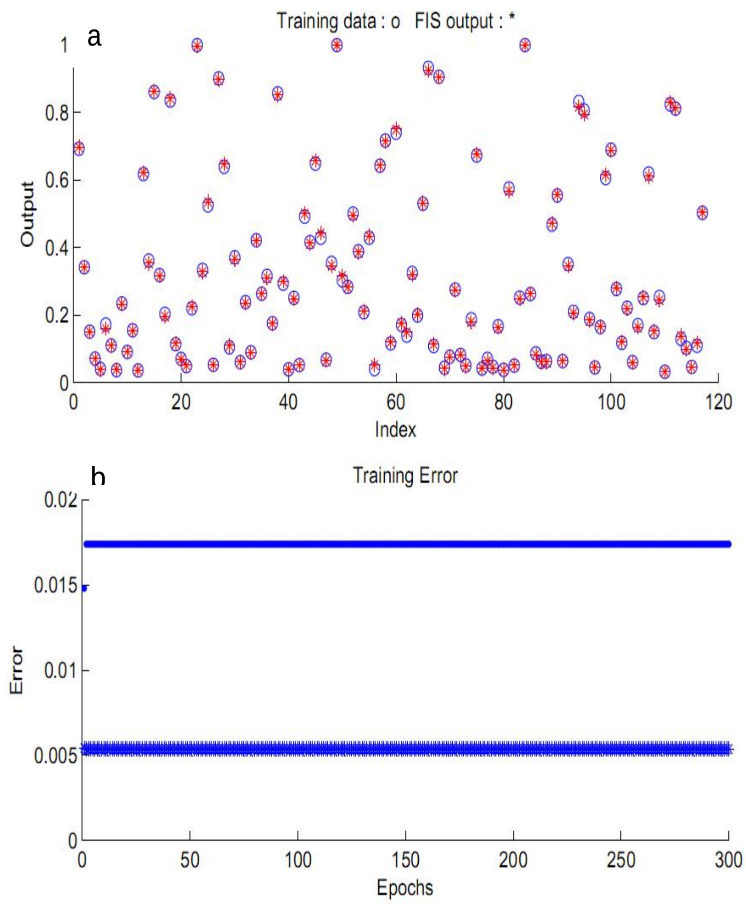

Fig. 4. (a) Comparison of training data with the output of developed FIS, (b) effect of the number of epochs on error obtained for trained network

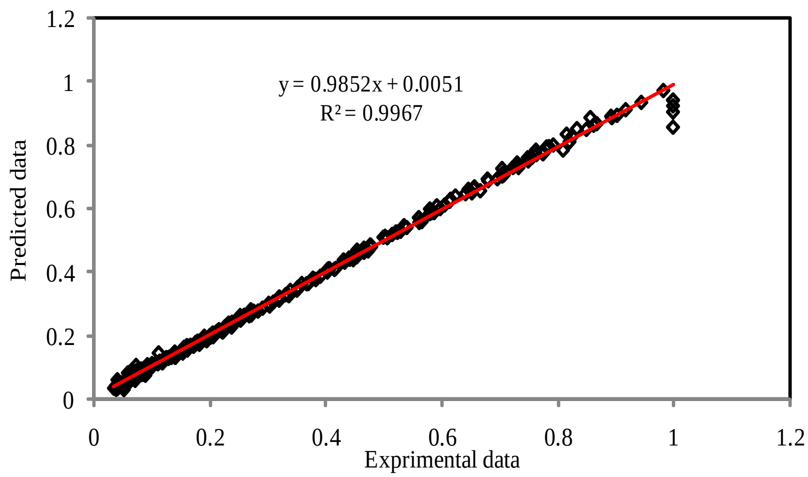

Fig. 5. Experimental against predicted values of MR by ANFIS model for the test data set (R^2 = 0.9967 and *RMSE* = 0.0161).

Figure 6 indicates two three-dimensional surfaces obtained after running the ANFIS model developed. As a result, the data show that decrease in slice thickness and increase in drying temperature both diminish the moisture content with increasing drying time. Ziaforoughi *et al.* (2016) reported similar results in the case of the effect of drying time and temperature using ANFIS model for infrared drying of quince slices. Yuzgec et al. (2009) developed an ANFIS model for fluidized bed drying to model Baker's yeast production to predict the yield of dry product and product temperature. It was found that the overall performance of ANFIS model was better than the three other conventional modeling tools (R^2 = 0.815-0.985). Al-Mahasneh *et al.* (2016) applied ANFIS in comparison with conventional thin-layer drying models to estimate moisture ratio in open sun drying of roasted green wheat. ANFIS represented higher performance in comparison with two-term exponential mode with RMSE = 1.2×10^{-6} and R^2 = 0.999 and *RMSE* = 0.038 and R^2= 0.988, respectively.

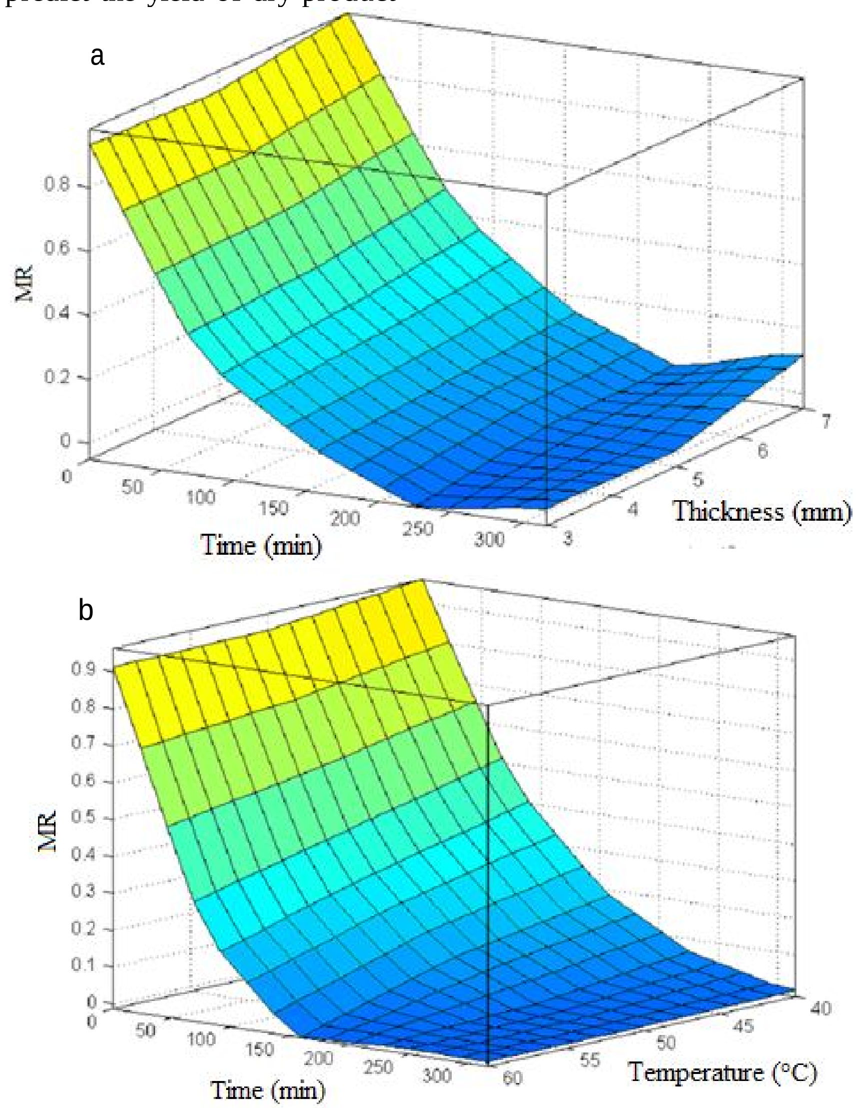

Fig. 6. Three-dimensional surface for the ANFIS model using two input variables of (a) time and thickness, (b) time and temperature.

GA-ANN model

GA-ANN model was developed for estimation of the moisture content obtained during hot-air drying of papaw slices in the cabinet dryer. To find the optimal network configuration, the number of neurons in hidden layer of ANN structure was changed by GA. The results revealed that GA-ANN model with 7 neurons in one hidden layer (topology of 3-7-1) could precisely estimate the amount of moisture content for the drying process of thin-layer papaw slices (R^2 = 0.9936 and *RMSE* = 0.0220). The experimental data *vs.* predicted data by the best GA-ANN models are shown in Fig. 7.

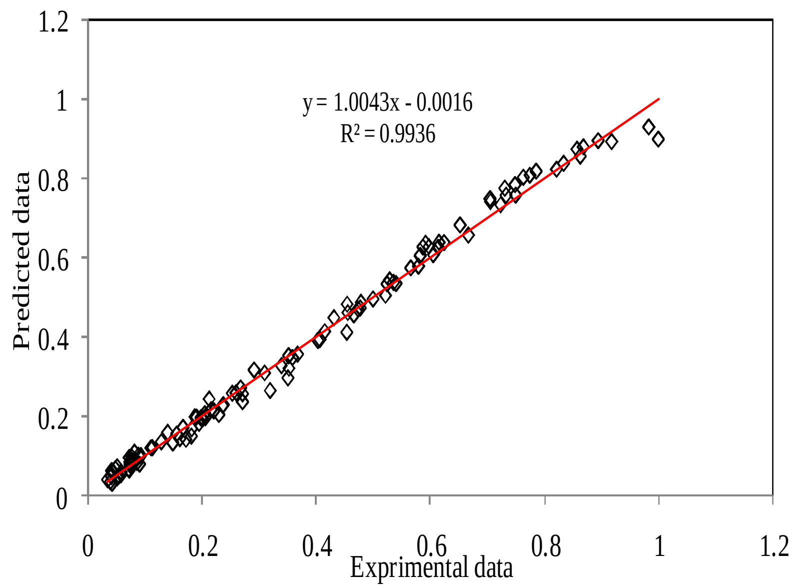

Fig. 7. Experimental against predicted values of MR by GA-ANN model for the test data set (R^2 = 0.9936 and *RMSE* = 0.0220).

It can be seen from Fig. 7 that the predicted data are highly similar to the experimental ones, indicating high efficiency of GA-ANN models used in prediction. Table 1 shows the weights and bias extents of the best GA-ANN models used, which could be applied in a computer program for prediction of the amount of moisture content during the drying process.

It can be observed that among the selected inputs, thickness was the most sensitive factor for estimation of the MR of papaw slices, followed by drying temperature and time. It means that the amount of moisture content for the papaw slices during hot-air drying were remarkably affected by thickness than the other studied favtors. Based on the literature review, the GA-ANNs had been a precise and appropriate instrument for modeling of drying process of banana (Mohebbi *et al.*, 2011), kiwifruit (Fathi *et al.*, 2011) and button mushroom (Salehi *et al.*, 2017) slices. Yolmeh *et al.* (2014) developed ANFIS and GA-ANN models to model the influence of annatto dye on *Salmonella enteritidis* population in mayonnaise using three inputs (annatto dye concentration at 0, 0.1, 0.2 and 0.4 %, storage time of 1–20 days and storage temperatures at 4 and 25 °C). Their results showed that both ANFIS and GA-AN N were able to predict *S.enteritidis* population with high accuracy of 0.998 and 0.999, respectively. The high performance of GA-ANN based model even reported in the case of prediction of amount of glucose release during *in vitro* gastrointestinal digestion of native and chemically modified starches (r = 0.984-0.993 and *RMSE* = 0.338-0.588) (Yousefi and Razavi, 2017)

Table 1. The bias and weights values for the optimized GA-ANN models obtained

Hidden neurons	Bias	Input neurons			Output neurons
		Time	Temperature	Thickness	Moisture ratio (MR)
1	0.942	0.680	-0.177	0.110	-0.266
2	0.358	0.011	0.135	1.158	0.597
3	-0.801	0.082	-2.647	0.069	0.429
4	-2.464	-1.511	0.064	-0.011	0.876
5	-0.140	-0.716	-0.002	0.448	0.002
6	1.145	0.341	-0.062	0.274	-0.442
7	-0.211	-1.068	0.239	-0.106	-0.177
Bias					0.437

In addition, in this study to find the sensitiveness of GA-ANN models used toward the selected inputs, sensitivity analysis was performed (Fig. 8). The sensitivity analysis demonstrates that which of the inputs has the greatest influence on the output and has more control on the amount of output.

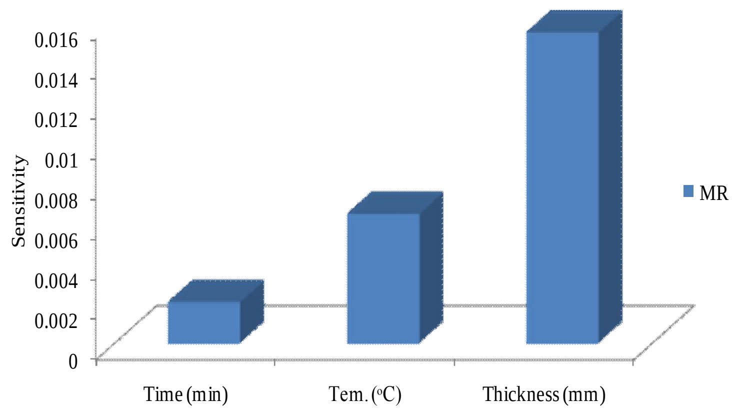

Fig. 8. The sensitivity of moisture ratio (MR) to the input variables.

Estimation of effective diffusivity coefficient

It is reported that the drying characteristics of biological products in falling rate period can be described by using Fick's second law of diffusion (Falade and Solademi, 2010). Crank (1975) solved this equation and introduced the Eq. (6), which can be used for slab geometry with uniform initial moisture diffusion, constant diffusivity and insignificant shrinkage:

$$MR = \frac{8}{\pi^2}\sum_{n=0}^{\infty}\frac{1}{(2n+1)^2}\exp\left(-\frac{(2n+1)^2\pi^2 D_{eff} t}{4L^2}\right) \qquad (6)$$

In this equation, D_{eff} is the effective diffusivity (m^2/s); n is positive integer, t is drying time, and L is the half thickness of the slab in samples (m). In practice, only the first term in Eq. (6) is used yielding:

$$MR = \frac{8}{\pi^2}\exp\left(-\frac{\pi^2 D_{eff} t}{4L^2}\right) \qquad (7)$$

Therefore, D_{eff} can be calculated from the slope of Eq. (7) using natural logarithm plot of MR versus drying time.

The calculated D_{eff} values for different drying temperatures are shown in Fig. 9. D_{eff} value for papaw slices increased with air temperature. This value for papaw slices was within the range of 6.93×10^{-10} to 1.50×10^{-9} m^2/s over the temperature range. It has been reported that the D_{eff} value for food materials is within the range of 10^{-11} to 10^{-9} (Sadin et al., 2014). The results obtained were in agreement with the results of other studies (Doymaz, 2007; Kaleemullah and Kailappan, 2005; Sacilik *et al*., 2006).

The effective moisture diffusivity represents overall mass transport of moisture in the material, including liquid diffusion, vapor diffusion, or any other possible mass transfer mechanism (Afzal and Abe, 1998).

Estimation of activation energy

The dependence of D_{eff} to temperature can be explained using the Arrhenius-type relationship (Simal et al., 1996). This matter is shown in the following equation:

$$D_{eff} = D_0 \exp\left(-\frac{E_a}{R(T+273.15)}\right) \quad (8)$$

In this equation, D_0 is the pre-exponential factor of Arrhenius equation (m^2s^{-1}), E_a is the activation energy (kJ/mol), T is the drying temperature (°C) and R is the gas constant (kJ/(mol.K)).

The E_a can be calculated from the slope of the plot on ln (*Deff*) vs. 1/ (T+273.15) (Fig. 10). This value was 32.5 (kJ/mol) for papaw slices. This value was lower than the E_a of green peppers drying (51.4 kJ/ mol) (Kaymak-Ertekin, 2002), mint drying (82.93 kJ/mol) (Park et al., 2002), but was higher than that of red chillies drying (24.47 kJ/ mol) (Kaleemullah and Kailappan, 2005).

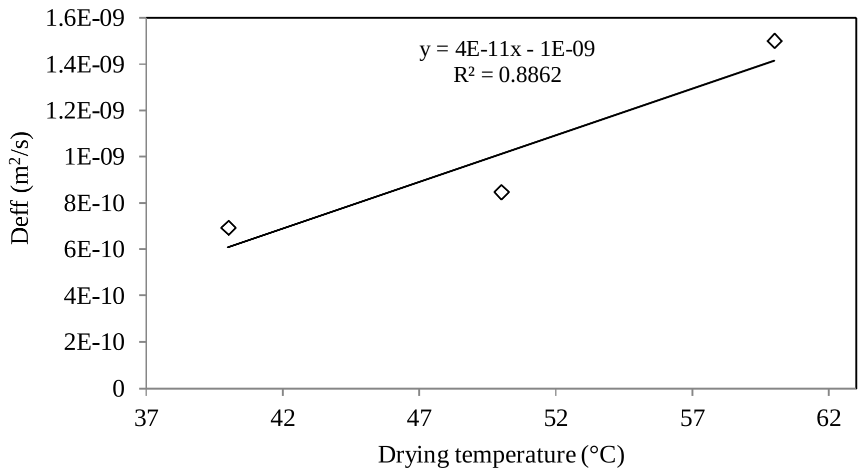

Fig. 9. Effect of drying temperature on the effective moisture diffusivity in papaw slices.

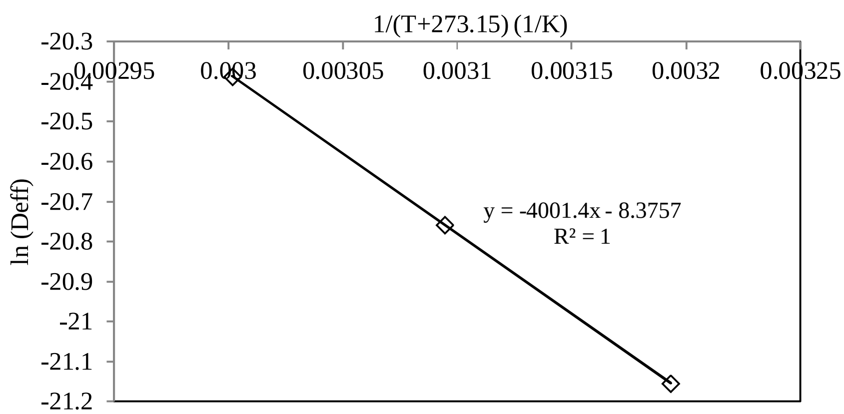

Fig. 10. Effect of drying temperature on the effective moisture diffusivity for calculation of activation energy.

Conclusions

The proficiency of ANFIS and GA-ANN modeling techniques for estimation of moisture content of papaw slices (3, 5 and 7 mm) during hot-air drying (40, 50 and 60 °C) was investigated. Accordingly, the results demonstrated that ANFIS model with three triangular type MFs (trimf) for all input variables (drying time, drying temperature, slice thickness) and linear for output (moisture ratio) gives the best fitting with the experimental data, which made it possible to predict the MR with high precision (R^2 = 0.9967 and *RMSE* = 0.0161). In addition, it was found that GA-ANN technique with 1 hidden layer including 7 neurons (topology of 3-7-1), predicts the nearest data to the experimental data (R^2 = 0.9936 and *RMSE* = 0.0220). More sensitivity of MR to slice thickness observed in this study demonstrates that this factor plays more significant role in hot-air drying process of papaw.

References

Afzal, T., Abe, T. 1998. Diffusion in potato during far infrared radiation drying. *Journal of food engineering*. 37, 353-365.

Aghdam, S., Yousefi, A., Mohebbi, M., Razavi, S., Orooji, A., Akbarzadeh-Totonchi, M. 2015. Modeling for drying kinetics of papaya fruit using fuzzy logic table look-up scheme. *International Food Research Journal*. 22.

Akgun, N.A., Doymaz, I. 2005. Modelling of olive cake thin-layer drying process. *Journal of Food Engineering*. 68, 455-461.

Al-Mahasneh, M., Aljarrah, M., Rababah, T., Alu'datt, M. 2016. Application of Hybrid Neural Fuzzy System (ANFIS) in Food Processing and Technology. *Food Engineering Reviews*. 8, 351-366.

Bahramparvar, M., Salehi, F., Razavi, S. 2014. Predicting total acceptance of ice cream using artificial neural network. *Journal of Food Processing and Preservation*. 38, 1080-1088.

Bala, B., Ashraf, M., Uddin, M., Janjai, S. 2005. Experimental and neural network prediction of the performance of a solar tunnel drier for drying jackfruit bulbs and leather. *Journal of Food Process Engineering*. 28, 552-566.

Crank, J. 1975. The Mathematics of Diffusion: 2d Ed. Clarendon Press.

Demirtas, C., Ayhan, T., Kaygusuz, K. 1998. Drying behaviour of hazelnuts. *Jo*urnal of the Science of Food *and Agriculture*. 76, 559-564.

Diamante, L., Munro, P. 1991. Mathematical modelling of hot air drying of sweet potato slices. *International journal of food science & technology*. 26, 99-109.

Doymaz, I. 2007. The kinetics of forced convective air-drying of pumpkin slices. *Journal of food engineering*. 79, 243-248.

Erenturk, K., Erenturk, S., Tabil, L.G. 2004. A comparative study for the estimation of dynamical drying behavior of Echinacea angustifolia: regression analysis and neural network. *Computers and Electronics in Agriculture*. 45, 71-90.

Falade, K.O., Solademi, O.J. 2010. Modelling of air drying of fresh and blanched sweet potato slices. *International journal of food science & technology*. 45, 278-288.

Fathi, M., Mohebbi, M., Razavi, S.M. 2011. Effect of osmotic dehydration and air drying on physicochemical properties of dried kiwifruit and modeling of dehydration process using neural network and genetic algorithm. *Food and bioprocess technology*. 4, 1519-1526.

Fernandes, F.A., Rodrigues, S., Gaspareto, O.C., Oliveira, E.L. 2006. Optimization of osmotic dehydration of papaya followed by air-drying. *Food Research International*. 39, 492-498.

Haghi, A., Amanifard, N. 2008. Analysis of heat and mass transfer during microwave drying of food products. *Brazilian Journal of Chemical Engineering*. 25, 491-501.

Irani, R., Nasimi, R. 2011. Evolving neural network using real coded genetic algorithm for permeability estimation of the reservoir. *Expert Systems with Applications*. 38, 9862-9866.

Izadifar, M., Mowla, D. 2003. Simulation of a cross-flow continuous fluidized bed dryer for paddy rice. *Journal of Food Engineering*. 58, 325-329.

Kaleemullah, S., Kailappan, R. 2005. Drying kinetics of red chillies in a rotary dryer. *Biosystems*

Engineering. 92, 15-23.

Kaymak-Ertekin, F. 2002. Drying and rehydrating kinetics of green and red peppers. *Journal of Food Science*. 67, 168-175.

Lenart, A. 1996. Osmo-convective drying of fruits and vegetables: technology and application. *Drying technology*. 14, 391-413.

Liu, Y.A., Baughman, D.R. 1995. Neural Networks in Bioprocessing and Chemical Engineering. *Academic Press*, Inc., San Diego.

Midilli, A., Kucuk, H., Yapar, Z. 2002. A new model for single-layer drying. *Drying technology*. 20, 1503-1513.

Mohebbi, M., Shahidi, F., Fathi, M., Ehtiati, A., Noshad, M. 2011. Prediction of moisture content in pre-osmosed and ultrasounded dried banana using genetic algorithm and neural network. *Food and Bioproducts Processing*. 89, 362-366.

Park, K.J., Vohnikova, Z., Brod, F.P.R. 2002. Evaluation of drying parameters and desorption isotherms of garden mint leaves (*Mentha crispa* L.). *Journal of Food Engineering*. 51, 193-199.

Prakash, O., Kumar, A. 2014. ANFIS modelling of a natural convection greenhouse drying system for jaggery: an experimental validation. *International Journal of Sustainable Energy*. 33, 316-335.

Sacilik, K., Keskin, R., Elicin, A.K. 2006. Mathematical modelling of solar tunnel drying of thin layer organic tomato. *Journal of food Engineering*. 73, 231-238.

Sadin, R., Chegini, G.-R., Sadin, H. 2014. The effect of temperature and slice thickness on drying kinetics tomato in the infrared dryer. *Heat and Mass Transfer*. 50, 501-507.

Salehi, F., Kashaninejad, M., Mahoonak, A., Ziaiifar, A. 2017. Drying of Button Mushroom by Infrared-Hot Air System. I*ranian Jounal of Food Science and Technology*. 13, 151-159.

Simal, S., Mulet, A., Tarrazo, J., Rosselló, C. 1996. Drying models for green peas. *Food Chemistry*. 55, 121-128.

Tao, Y., Li, Y., Zhou, R., Chu, D.-T., Su, L., Han, Y., Zhou, J. 2016. Neuro-fuzzy modeling to predict physicochemical and microbiological parameters of partially dried cherry tomato during storage: effects on water activity, temperature and storage time. *Journal of food science and technology*. 53, 3685-3694.

Tripathy, P., Kumar, S. 2009. Neural network approach for food temperature prediction during solar drying. I*nternational Journal of Thermal Sciences*. 48, 1452-1459.

Vergara, F., Amezaga, E., Barcenas, M., Welti, J. 1997. Analysis of the drying processes of osmotically dehydrated apple using the characteristic curve model. *Drying Technology*. 15, 949-963.

Yolmeh, M., Najafi, M.B.H., Salehi, F. 2014. Genetic algorithm-artificial neural network and adaptive neuro-fuzzy inference system modeling of antibacterial activity of annatto dye on Salmonella enteritidis. *Microbial pathogenesis*. 67, 36-40.

Yousefi, A., Asadi, V., Nassiri, S.M., Niakousari, M., Aghdam, S.K. 2013a. Comparison of mathematical and neural network models in the estimation of papaya fruit moisture content. T*he Philippine Agricultural Scientist*. 95.

Yousefi, A., Niakousari, M., Moradi, M. 2013b. Microwave assisted hot air drying of papaya (*Carica papaya* L.) pretreated in osmotic solution. *African Journal of Agricultural Research*. 8, 3229-3235.

Yousefi, A., Razavi, S.M. 2017. Modeling of glucose release from native and modified wheat starch gels during in vitro gastrointestinal digestion using artificial intelligence methods. *International Journal of Biological Macromolecules*. 97, 752-760.

Yuzgec, U., Becerikli, Y., Turker, M. 2009. Comparison of different modeling concepts for drying process of baker's yeast. IEEE T*ransactions on Neural Networks*. 19, 1231-1242.

Ziaforoughi, A., Yousefi, A.R., Razavi, S. 2016. A Comparative Modeling Study of Quince Infrared Drying and Evaluation of Quality Parameters. *International Journal of Food Engineering*. 12, 901-910.

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تخمین میزان محتوای رطوبتی میوه پاپایا با استفاده از سیستم تلفیقی عصبی-فازی و الگوریتم ژنتیک-شبکه عصبی

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چکیده

در این تحقیق از سیستم تلفیقی عصبی-فازی (ANFIS) و الگوریتم ژنتیک-شبکه عصبی (GA-ANN) برای مدلسازی سینتیک خشک شدن ورقه‌های پاپایا به وسیله هوای داغ استفاده گردید. ورودی های سیستم مدلسازی شامل سه ورودی زمان خشک شدن (320-0 دقیقه)، دمای خشک شدن (40، 50 و 60 درجه سانتیگراد) و ضخامت ورقه‌ها (3، 5 و 7 میلی متر) و خروجی سیستم شامل نسبت رطوبتی (MR) بود. در طراحی سیستم مدلسازی ANFIS از توابع عضویت مثلثی و 27 قانون استفاده گردید. نتایج نشان داد که داده های پیش بینی شده توسط سیستم ANFIS دارای تطبیق بالایی با نتایج آزمایشگاهی بود (R^2= 0.9967, RMSE= 0.0161). همچنین سیستم مدلسازی GA-ANN بهینه شده، شامل 7 نرون در لایه مخفی، با دقت بالایی میزان رطوبت را پیش‌بینی نمود (R^2= 0.9936, RMSE= 0.0220). ضریب انتشار موثر ورقه‌های پاپایا در بازه دمایی مورد آزمایش بین 10^{-10}× 6.93 و 10^{-09}× 1.50 مترمربع بر ثانیه تعیین شد. همچنین مقدار بدست آمده برای انرژی فعالسازی (32.5 کیلوژول بر مول) به خوبی تاثیر دمای خشک کردن بر روی ضریب انتشار را نشان داد.

واژه های کلیدی: سیستم تلفیقی عصبی-فازی، الگوریتم ژنتیک-شبکه عصبی، پاپایا

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