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Optimization of infrared-convective drying of white mulberry fruit using response surface methodology and development of a predictive model through artificial neural network

Iman Golpour[a*], Mohammad Kaveh[b], Reza Amiri Chayjan[c] & **Raquel P. F. Guiné[d,e]**

[a] Department of Mechanical Engineering of Biosystems, Urmia University, Urmia, Iran

[b] Department of Biosystems Engineering, University of Mohaghegh Ardabili, Ardabil, Iran

[c] Department of Biosystems Engineering, Faculty of Agriculture, Bu-Ali Sina University, Hamedan, Iran

[d]CI&DETS, Polytechnic Institute of Viseu, Portugal

[e]CITAB, University of Trás-os-Montes, Vila Real, Portugal

[*]**Corresponding author:** Iman Golpour, Department of Mechanical Engineering of Biosystems, Urmia University, Urmia, Iran.

Email address: Imangolpour@gmail.com; **Tel**: (+98) 32752740; **Fax**: (+98) 32753172

ABSTRACT

In this research, a comparative approach was carried out between artificial neural networks (ANNs) and response surface methodology (RSM) to optimize the drying parameters during infrared–convective drying of white mulberry. The drying experiments were performed at different air temperatures (40, 55 and 70 °C), air velocities (0.4. 1 and 1.6 m/s) and infrared radiation power (500, 1000 and 1500 W). RSM focuses on maximization of effective moisture diffusivity (D_{eff}) and minimization of specific energy consumption (SEC) in the drying process. The optimized conditions were encountered for the air temperature of 70 °C, the air velocity of 0.4 m/s and the infrared power level of 1464.57 W. The optimum values of D_{eff} and SEC were 1.77×10^{-9} m^2/s and 166.554 MJ/kg, respectively, with the desirability of 0.9670. Based on the statistical indices, the results showed that the Feed and Cascade Forward Back Propagation neural systems with application of Levenberg–Marquardt training algorithm and topologies of 3-20-20-1 and 3-10-10-1 were the best neural models to predict D_{eff} and SEC, respectively.

Keywords White mulberry. Effective moisture diffusivity. Specific energy consumption, Response surface methodology. Artificial neural network

Introduction

White mulberry (*Morus* sp.), a genus of family Moraceae, is a fruit producing tree that can grow in a wide range of climatic, topographical and soil conditions (Huang et al., 2011). Mulberry fruit is used for making confectionery products such as jam, marmalade, pulp and paste (Vijayan et al., 2011).

Drying is one of the oldest and most common methods used to preserve foods and it can be carried out either traditionally, by sun drying, or industrially by solar, hot air, infrared and other drying methods (Afolabi et al., 2015; Doymaz et al., 2016). Convective drying can improve energy efficiency and control the drying temperature and air humidity, which could be appropriate for temperature sensitive vegetables and fruits (Fan et al., 2014; Liu et al., 2015). Infrared radiation (IR) has received much attention recently, because it constitutes one possible tool for that purpose (Hammouda and Mihoubi, 2014). IR technology for drying of foods could decrease drying time, maintain uniform temperature in the product and provide better-quality products (Song et al., 2016; Salehi and Kashaninejad, 2018b). The increase in the demand for high-quality shelf-stable dried fruits and vegetables requires the design, modeling and optimization of the drying processes, targeting the ultimate quality of the dried product while at the same time maximizing the efficiency of the process (Fealekari and Amiri Chayjan, 2014).

Response surface methodology (RSM) has been effectively employed in process and product improvement for experimental design and model development of food processing, due to the complexity of the reactions and nonhomogeneous structure of food products (Aghilinategh et al., 2015). Modeling and optimizing of the process are vital factors in drying technology to increase efficiency of the drying facilities. RSM has been repeatedly used to optimize food processes. In a research work, Sumic et al. (2016) employed RSM to optimize the parameters for vacuum drying of red currants. The results of the study showed the optimal conditions for that process to be temperature of 70.2 °C, pressure of 39 mbar and drying time of 8 h. The use of RSM for optimization of osmo-vacuum drying of pear by Amiripour et al. (2015) evidenced the optimal conditions for moisture content, rehydration ratio and shrinkage to be 23.26 % (w.b.), 1.46 and 67.45 %, respectively. Amiri Chayjan et al. (2017) investigated the optimization of pistachio nut drying in a fluidized bed dryer with microwave pretreatment applying RSM. According to their results, the optimum values of effective diffusivity (D_{eff}), shrinkage and specific energy consumption (SEC) were 4.865×10^{-9} m^2/s, 14.22 %, and 2.164 kWh, respectively.

Artificial neural networks (ANNs) constitute an alternative approach to solve problems, and their use has been increasing due to the possibility of outperforming traditional models. ANNs have been utilized successfully mainly due to their ability to adjust multivariable nonlinear functions (Silva et al., 2015; Golpour et al., 2015). In the field of drying processes, the neural networks are frequently used to model and predict the behavior of various products. Kaveh and Chayjan, (2015) predicted moisture ratio (MR), drying rate (DR), specific energy consumption, effective diffusivity and shrinkage for terebinth using fluidized bed dryer by ANNs. They showed that the highest values of R^2 obtained were 0.9965, 0.9730, 0.9855, 0.9932 and 0.9917, respectively for MR, DR, SEC, D_{eff} and shrinkage. Accordingly, Taghinezhad et al. (2019) used ANNs for prediction of effective moisture diffusivity, specific energy consumption, color and shrinkage in quince drying. The results of the research work showed ANNs had good predictive capability with values of R^2 higher than 0.97 for predicting all parameters.

Concerning the proper combinations of air temperature, infrared power and air velocity for optimum responses in combined convective and infrared drying, limited studies have been done up to now. Therefore, the overall objective of this study was to develop a predictive optimization model by coupling the two approaches of ANN and RSM as an alternative to conventional procedures to predict the optimal conditions for the convective–infrared drying parameters of mulberry fruit, leading to minimum specific energy consumption and to maximum moisture diffusivity.

Materials and methods

Sample Preparation

White mulberry fruits were obtained from the forests of Nalas city, West Azarbaijan province, Iran, in June 2018. The white mulberry samples were cleaned and stored at a refrigeration temperature of 4 ± 1°C. The initial moisture content of the fresh white mulberry samples was 2.43% (d.b.) that was determined in triplicate by applying a hot air oven at 70 °C for 24 h, allowing reaching constant weight (Kaveh et al., 2018). About 40 g of mulberry fruits were used in each experiment.

Drying equipment

For this study, a laboratory infrared–convection dryer was developed at the Biosystems Engineering Department of Bu-Ali Sina, University, Hamedan, Iran (Figure 1). The essential parts of the drying system mainly consisted of an adjustable centrifugal blower, four infrared lamps (Philips, Belgium) with 2000 W power, electrical air heating chamber (2.4 kW), drying chamber, inverter (LS, Korea), thermostat (Atbin, Iran) and a tray sample. Mean values of air ambient temperature and relative humidity were variable in the ranges 25 to 31°C and 24% to 29%, respectively. During the drying experiments, the ambient air temperature, air relative humidity and inlet and outlet temperatures of the drying chamber were recorded at every 2 minutes. After 30 min, when the conditions inside the drier reached the steady state, the dryer was loaded with 40±1 g of white mulberry and drying started. Experiments were performed at 40, 55 and 70°C. For each air temperature, three air velocities (0.4, 1.0 and 1.6 m/s) and three IR lamp radiations (500, 1000 and 1500 W) were used. Samples were weighed during the drying process by a digital balance (AND GF6000, Japan) with 0.01 g accuracy. The drying process continued until the final moisture content fell from an initial moisture of about 2.43% (d.b.) to or below 0.15% (d.b.).

Effective moisture diffusivity

Fick's second law is usually used to describe the drying characteristics of biological products during falling rate periods in diffusion mode (Cruz et al., 2015; Golpour et al., 2017).

The effective moisture diffusivity (D_{eff}) can be estimated based on the drying data through Eq. (1), that applies to samples comparable to an infinite slab (Guiné et al., 2011).

$$MR = \frac{(M_t - M_e)}{(M_0 - M_e)} = \sum_{n=1}^{\infty} \frac{4}{b_n^2} \exp\left[-D_{eff} \frac{b_n^2 t}{r^2} \right] \tag{1}$$

where, MR is the dimensionless moisture ratio, M_t is the moisture content at any time (% d.b.), M_e is the equilibrium moisture content (% d.b.), M_0 is the initial moisture content (% d.b.), b_n is the number of terms taken into consideration, t is the drying time (s), D_{eff} is the effective moisture diffusivity (m^2/s). Moisture ratio (MR) can be simplified to $\frac{M_t}{M_o}$ because M_e was relatively small compared to M_t and M_0 (Omolola et al., 2018). If the second and following terms in the sum in Eq. (2) are neglected due to their small contribution, then the equation can be written in the logarithmic form as (Mota et al., 2010):

$$\ln(MR) = \ln(\frac{4}{b_n^2}) - D_{eff} \frac{b_1^2}{r^2} t \tag{2}$$

The slope (K_1) is calculated by plotting t against $\ln(MR)$ as follows:

$$K_1 = -D_{eff}\frac{b_1^2}{r^2} \tag{3}$$

Specific energy consumption

The total energy needed for drying one charge of the drier together with the energy requirements for drying 1 kg of fresh mulberry fruit were computed for each drying experiment by the following Eq. (4) (Kaveh et al., 2018):

$$SEC = \left(\frac{Qt}{m_v}\right)\left(\frac{(C_{pa} + C_{pv}h_a)}{V_h}\right)(T_{in} - T_{am}) \tag{4}$$

where SEC is the specific energy consumption (kJ/kg) at each set of experimental conditions, Q is the inlet air flow to drying chamber (m^3/min), t is the total drying time (min), m_v is the mass of removed water (kg), C_{pv} and C_{pa} are the specific heat capacity of vapor and air, respectively (1,004.16 and 1,828.8 J/kg.°C), h_a is the air absolute humidity ($kg_{vapor}/kg_{dry\ air}$), V_h is the air specific volume (m^3/kg) and T_{in} and T_{am} are the air temperatures, entering the chamber and in the ambient surrounding (°C), respectively.

Response surface methodology modeling

Experimental design

The effect of three independent variables, A (air temperature), B (air velocity) and C (infrared power), on two responses (effective moisture diffusivity and specific energy consumption) was evaluated by RSM. In total, 20 experiments were established based on a face-centered central composite design (FCCD) by applying the design expert statistical software (V7) for simultaneous optimization of the multiple responses. These 20 experiments were generated including six replicates of the center point to calculate the repeatability of the method.

Table 1 shows the levels of each independent variable applied, whereas the combination of variables and the corresponding responses for RSM analysis are shown in Table 2. In this design of experiments, three coded levels for each variable were selected: -1, 0 and +1 corresponding to the low, medium and high levels for each independent variable, respectively (Table 1). The central values (level zero) chosen for experiment design to develop the regression equation were 55 ºC for air temperature, 1 m/s for air velocity and 1000 W for infrared power.

Model development

The obtained models were developed from regression coefficients under a range of experimental factors. The behavior of the response surface was studied for each of the response variables (Y_i). The experimental data were fitted to a quadratic polynomial model which allowed estimating the regression coefficients. The generalized quadratic polynomial model proposed to predict the response variables is as follows:

$$Y_i = \beta_0 + \beta_A A + \beta_B B + \beta_C C + \beta_{AA} A^2 + \beta_{BB} B^2 + \beta_{CC} C^2 + \beta_{AB} AB + \beta_{AC} AC + \beta_{BC} BC \qquad (5)$$

where β_0, $\beta_{A,B,C}$, $\beta_{AA,BB,CC}$, and $\beta_{AB,AC,BC}$ are the interaction coefficients of constant, linear, quadratic and the second-order terms, respectively, while A, B, C are the coded independent variables for air temperature, air velocity and Infrared power. Modeling started with a quadratic model including linear, squared and interaction terms, and the adequacies of model were checked in terms of the values of R^2, adjusted R^2, and prediction error sum of squares (PRESS).

Statistical analysis

The ranges and levels of independent variables are presented in Table 2. The experimental plan for optimization included three dependent variables: temperature (40, 55 and 70 °C), air velocity (0.4, 1 and 1.6 m/s) and infrared power (500, 1000 and 1500 W). All experiments were replicated three times. Using software Design Expert (V7), analysis of regression and statistical analysis of variance (ANOVA) were conducted by fitting Eq. (5) to the experimental data to evaluate the regression coefficients and statistical significance of model terms. Also, ANOVA was implemented for checking the adequacy and accuracy of the fitted models (Changrue et al., 2017). The significance of the model terms was assessed by F-ratio at a probability (P) of 0.05. The values of R^2, adjusted-R^2, predicted error sum of squares (PRESS) and lack-of-fit of models were evaluated to check the model adequacies. The regression coefficients were employed to establish statistical computations for generating the response surface plots from the regression models. Finally, the optimum values of the selected variables were obtained by solving the regression equation and by analyzing the response surface contour plots.

Optimizing the drying process

The desired goal for each independent variable and response was established. The independent variables were kept within the range of experimental conditions selected while the responses were set to maximum for diffusivity and minimum for SEC. Equal weights were assigned to each goal to adjust the shape of desirability function for optimization of the multiple responses (Table 3). Second order polynomial models were used in this study for each response to determine the specified optimum conditions.

In order to find an optimum solution, the goals were combined into an overall composite function D(x), called desirability function, whose value for n responses, which can be defined as (Fealekari and Amiri Chayjan, 2014):

$$D(x) = (d_1 \times d_2 \times d_3 \times d_4 \times d_5 .... \times d_n)^{1/n} \quad (6)$$

For any response, the desirability can vary from a minimum of zero, when one or more responses fall outside the desirable limits, to a maximum of one, which is the ideal case.

ANN design

The schematic structure of ANNs used in this research work to predict the diffusivity and SEC is shown in Figure 2. Input variable levels, boundaries and levels of input parameters are shown in Table 4. In this study, the neural network toolbox using the 2017 version of MATLAB software was used to predict output variables. The 27 data patterns, achieved from various experimental data, were randomly divided into 19 (70%) and 8 (30%), which were used for training and testing the neural networks, respectively (Kaveh et al., 2017; Golpour et al., 2015). The input layer had three neurons (air velocity, drying air temperature and infrared power) and the network output layer had one neuron (diffusivity or SEC). The number of neurons varied from 2 to 20 in both hidden layers.

A multilayer perceptron (MLP) neural network with different hidden layers (one and two) was trained and tested. MLP is a layered feed forward back propagation (FFBP) and cascade forward back propagation (CFBP) network typically trained with static back propagation. Its main advantages are easiness to use and approximation of any input/output parameters.

In this work was examined the effect of several error minimization algorithms, such as Bayesian regulation (BR) and Levenberg-Marquardt (LM), on the performance of the ANN model. Different transfer functions, like the hyperbolic tangent sigmoid (TANSIG), the logarithmic sigmoid (LOGSIG), and linear (PURELIN), were used to assess the neuron output. After using appropriate learning algorithms and transfer functions, the effect of neuron number and training epochs on ANN performance were studied. To develop a statistical model, networks were trained three times and the best values were recorded for each parameter.

About 70% of the experimental data were separated for network training to find a suitable structure. The goodness of fit of the optimal ANN was based on coefficient of determination (R^2), mean square error (MSE), and mean absolute error (MAE) for the tested models, as follows (Khazaei et al., 2013):

$$MSE = \frac{1}{nq}\sum_{p=1}^{n}\sum_{i=1}^{q}(S_{ip} - T_{ip})^2 \tag{7}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{m}\left[S_k - T_k\right]}{\sum_{k=1}^{m}\left[S_k - \frac{\sum_{k=1}^{n} S_k}{n}\right]} \tag{8}$$

$$MAE = \frac{100}{n}\sum_{k=1}^{m}\left|\frac{S_k - T_k}{T_k}\right| \tag{9}$$

where S_{ip} is the network output in i^{-th} neuron and p^{-th} pattern, T_{ip} is the target output at i^{-th} neuron and p^{-th} pattern, q is the number of output neurons, n is the number of training patterns, S_k is the network output for k^{-th} pattern and T_k is the target output for k^{-th} pattern.

To increase the accuracy and processing velocity of network, input data were normalized at domain of [0, 1].

Results and discussion

RSM modeling

The optimization of D_{eff} and SEC for dried white mulberry was based on maximizing D_{eff} and minimizing SEC. In order to reduce the number of parameters to be tested, several parameters were previously evaluated in a wide range of values prior to RSM optimization (Bachir bey et al., 2013). According to the results, a quadratic model was significant for obtaining the desired responses. The second-order polynomial equation was fitted to the experimental results obtained on the basis of a face-centered central composite design (FCCD).

Experimental design

The final modified quadratic models for relation between responses (D_{eff} and SEC) and input variables are given in Eqs. (10) and (11) in terms of coded factors:

$$\begin{aligned} D_{eff} &= 8.918\times10^{-10} + 3.443\times10^{-11}A + 7.630\times10^{-11}B + 3.270\times10^{-11}C \\ &- 2.154\times10^{-10}AB + 1.001\times10^{-10}AC - 1.529\times10^{-10}BC \\ &- 1.350\times10^{-10}A^2 + 1.720\times10^{-10}B^2 + 1.720\times10^{-10}C^2 \end{aligned} \quad (10)$$

$$\begin{aligned} SEC &= 525.87 + 83.17A + 219.32B - 78.80C + 48.14AB + 15.88AC \\ &- 41.77BC - 89.34A^2 - 71.63B^2 + 40.66C^2 \end{aligned} \quad (11)$$

where the values of parameters A, B, and C are defined in Table 2.

The equations aimed to determine the effect of individual variables or combination of several variables over the responses. Positive coefficient values reveal the positive interaction of factors and the impact on combined convective with infrared drying process, whereas the negative coefficient values point to the detrimental and interfering effect of the parameters on overall drying. From Eq. (10), it is clear that all individual factors (A, B, C) had a positive effect on the response of D_{eff}. All the linear variables, except infrared power (C), had a positive relation with SEC whereas the SEC raised with increasing air temperature (A) and air velocity (B) levels. Therefore, infrared power had a negative effect on SEC, increasing energy consumption and, consequently, the costs·

Effective moisture diffusivity response

Table 5 illustrates the ANOVA results for different drying experiments. The p-value accounts for the significance of each coefficient describing the interactions between the independent variables. The lower the p-values, the more significant are the model terms. For $p < 0.05$ the model term is significant (Das et al., 2014), considering 95% confidence. According to the results obtained, air temperature ($P < 0.0001$), air velocity ($P = 0.0109$) and infrared power ($P = 0.0038$), all had significant effect on D_{eff} (Table 5). Also, the interaction of air temperature with air velocity and infrared power had significant effect on D_{eff} but interaction of quadratic values of air velocity and air temperature had no significant effect on D_{eff} ($P > 0.05$) (Table 5).

The model F-value was calculated as ratio of mean square regression and mean square residue. The ANOVA for D_{eff} shows an F-value of 17.71, which is significant according to the corresponding p-value (Table 5). Coefficient of determination (R^2) and adjusted R^2 (adj-R^2) were calculated to check the adequacy and fitness of the model. According to the results presented in Table 6, for D_{eff} the quadratic model with $R^2 = 0.9410$ was the best model. The adequacy and fitness of the models were tested by ANOVA, and the results showed that the equation adequately represented the real relation between a set of independent variables and the responses (Tables 5, 6).

To visualize the combined effect of the two factors on the response, the response surface and contour plots were generated for each of the models in the function of two independent variables, while keeping the remaining independent variable at the central value (Figures. 3 a-c). Figure. 3 illustrates the 3D surface of D_{eff} versus air temperature, air velocity and infrared power. According to Figures. 3a and 3b, it was observed that both air temperature and velocity simultaneously influenced D_{eff}. With increasing air temperature, air velocity and infrared power, D_{eff} was increased. However, the effect of air temperature was more pronounced when compared with the other independent variables. Also, the effect of infrared power was more intense than that of air velocity. Increase in air temperature led to increasing the drying rate. Also at the initial stage of the drying process, when the water vapor at the surface of the sample was more concentrated, increasing air velocity led to higher mass transfer between the surrounding air and the samples and, subsequently, an increase in D_{eff} (Motevali and Tabatabaei, 2017). Similar results have been observed in drying of some agricultural products such as apple slices (Zhu et al., 2010), rough rice (Khir et al., 2011), soybean (Niamnuy et al., 2012), jujube (Chen et al., 2015), potato (Onwude et al., 2018). The increase in air temperature from 40 to 70 ^{o}C and air velocity from 0.4 to 1.6 m/s, increased D_{eff} to a maximum value of 1.77×10^{-9} m^2/s.

Specific energy consumption response

ANOVA results for SEC are shown in Table 7. The model can be considered as statistically significant if the p-value is lower than 0.05 and the value of F is high. The model F-value of

16.28 together with the very low p-value ($P < 0.0001$) for the dependent variable SEC implies that the model is significant.

The coefficient estimates and the corresponding p-values suggest that, among the independent variables used in the study, the linear terms A (air temperature), B (air velocity), and C (infrared power) ($P < 0.0001$) had the greatest effect on the response variable (SEC). The interaction of air temperature with air velocity and interaction of air velocity with infrared power ($P < 0.05$), quadratic value of air temperature ($P < 0.0001$), quadratic values of air velocity and quadratic values of infrared power, had significant effect on SEC. The statistical analysis gave high significant level, confirming the goodness of fit of the model in case of the SEC ($P < 0.0001$). The contribution of quadratic model was significant ($P<0.05$) for response of the dependent variable SEC (Table 7). The ANOVA analysis indicates a good model performance, with $R^2 = 0.9932$ for SEC (Table 8). A high coefficient of determination indicates that the variables adequately fit the regression equation, which means that the empirical model well described the variations during drying. The use of an adjusted R^2 (adj-R^2) aims to evaluate the model adequacy and fitness, by correcting the R^2 value for the sample size as well as the number of terms in the model. The adj-R^2 value (0.9870 for SEC) indicates a high fitting capacity of the model (Table 8).

The best way of expressing the effect of any independent variable on the SEC was to generate surface response plots of the model, which were done by varying two variables within the experimental range under investigation and holding the other variable at its central level (0 level). Effect of process parameters on SEC is shown in Figure 4. Minimum SEC was recorded when the air temperature, air velocity and infrared power were 40 ºC, 0.4 m/s and 150 W, respectively, while the maximum was at 70 ºC, 1.6 m/s and 500 W, respectively (Figure 4a-c).

Both air temperature and velocity exhibit a positive linear effect on SEC, whereas the infrared power exerts a negative linear effect, as shown in Figure 4a-c. Hence, SEC decreased substantially with increase in infrared power (Figure 4 b, c) and increased with increasing drying temperature and air velocity. Due to the reduction of water vapor in the surface of the samples, increase in drying rate and subsequently decrease in drying time, the lowest SEC was obtained at lowest air velocities. Similar results have been reported in drying shiitake mushroom (Kantrong et al., 2014) and apple (El-mesery and Mwithiga, 2015).

Optimization of process parameters

Optimum conditions for convective–infrared drying of mulberry were determined to obtain maximum D_{eff} and minimum SEC. Using the desirability function method, 20 solutions were obtained for the optimum covering indicators with desirability value of 0.9670. Optimum values of process variables were: 0.4 m/s for air velocity, 70°C for air temperature, and 1464.57 W for infrared power. The values of D_{eff} and SEC at these drying conditions were predicted as 1.77×10^{-9} m^2/s and 166.55 MJ/kg, respectively. The positive effect of temperature on D_{eff} leads to proposing high desirability. The study accomplished by Sharma and Prasad (Sharma and Prasad, 2006) proposed the maximum air temperature (70°C) for the optimization of microwave drying process of garlic. Also the maximum air temperature was selected for optimization of processing parameters of horse mackerel (Shi et al., 2008).

Artificial neural networks (ANNs)

Tables 9 and 10 summarize a list of the best neural network topology structures, threshold functions and different applied algorithms in predicting D_{eff} and SEC. Most applied topologies and threshold functions have proper training errors. Therefore, ANN is suitable for modeling the drying of white mulberry. The main reason for ANN convergence might be the large amount of the input patterns.

Two strategies, which included similar and various threshold functions for all layers, were used to study the effect of different threshold functions on FFBP and CFBP outputs (Tables 9 and 10). These strategies, together with learning algorithms of LM and BR, were used for training the FFBP and CFBP networks. Various topologies were chosen as the best results from each network, training algorithm and threshold functions.

Tables 9 and 10 present the results of ANN modeling of D_{eff} and SEC variations during drying of white mulberry samples. The effects of hidden layer number and neuron number in each hidden layer on precision of the predicting can be seen from the Tables. As shown in Table 9, among the applied networks for predicting D_{eff}, the FFBP network with a topology of 3-20-20-1, $R^2 = 0.9952$, $MSE = 0.0003$, TANSIG-TANSIG-TANSIG and LM training algorithm at 30 training epochs had the best estimation with minimum MSE.

Similar finding has been reported for the fluidized drying of pomegranate seed cultivars, in which case the D_{eff} was predicted using artificial neural network with R^2 = 0.9972 (Amiri chayjan et al., 2012). Also, Amiri Chayjan et al. (2012) reported the best results for FFBP neural network for D_{eff} of sour cherry drying belonged to TANSIG threshold function with LM algorithm with $R^2 = 0.9994$ in the first strategy.

Table 10 shows that, among the applied networks to predict the SEC the CFBP network with a topology of 3-10-10-1, $R^2 = 0.9899$, $MSE = 0.0008$, TANSIG-PURELIN-TANSIG and LM training algorithm in 15 epochs had the best estimation with the minimum MSE. These findings are in agreement with results reported by Kaveh et al. (2018) for drying properties of pistachio nuts, squash and cantaloupe seeds under fixed and fluidized bed using

Cascade forward back propagation network for predicting SEC with $R^2 = 0.9667$ at 60 training epochs.

Figure 5 compares for both variables D_{eff} and SEC the predicted values with the desired output values, using the optimal ANN, and shows the data points are banded around a 45° straight line, demonstrating the suitability of the selected static multilayer feed-forward ANNs for the infrared–convective drying of white mulberry. Therefore, it can be seen that the predicted energy consumption and D_{eff} by applying the optimal topology of ANN are very close to those of experiment data.

The findings of this study reveal that the optimized ANN model can certainly replace the mathematically constitutive models in predicting the drying parameters of mulberry fruit, because it takes passable efficiency of experimental data into account and automatically improves itself through learning. In addition, the ANN models have the capability to ameliorate their efficiency with results obtained from further new experiments, with or without new processing situations. This provides the gradual possibility of establishment of a singular powerful model which can be of premier significance in automatic control system.

Conclusions

This study reviews the performance of RSM and ANN methods for optimization of drying parameters and prediction of output variables (D_{eff} and SEC) using the experimental data in the infrared–convective drying of white mulberry. Based on the profiles of response surface, drying at higher air temperature, velocity and infrared power allowed obtaining higher values of D_{eff}, whereas higher retention of SEC was found for drying at lower infrared power. The results indicated that quadratic model could work well for the prediction of the two studied variables. Air temperature of 70 °C, air velocity of 0.4 m/s and infrared power of 1464.57 W were proposed as optimum independent variables. Optimum values of D_{eff} and SEC were 1.77×10^{-9} m^2/s and 166.554 MJ/kg, respectively, with a desirability of 0.9670. Taking into consideration the results from modeling analyses, it can be concluded that ANN and RSM models demonstrated reasonable performance in predicting D_{eff} and SEC. The results further showed that LM training algorithm of back-propagation with the minimum MSE was suitable for predicting the drying parameters. The values of the coefficient of determination were acceptable for both models ($R^2 = 0.9952$ for D_{eff} and $R^2 = 0.9899$ for SEC).

Compliance with ethical standards

Conflict of interest There are no conflicts to declare.

Compliance with ethical requirements This article does not contain any studies with human or animal subject.

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