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Prediction of Drying Time and Moisture Content of Wild Sage Seed Mucilage during Drying by Infrared System Using GA-ANN and ANFIS Approaches

Gh. Amini [a], ***F. Salehi*** [b*], ***M. Rasouli*** [c]

[a] MSc of the Faculty of Agriculture, Bu-Ali Sina University, Hamedan, Iran.
[b] Associate Professor of the Department of Food Science and Technology, Bu-Ali Sina University, Hamedan, Iran.
[c] Assistant Professor of the Faculty of Agriculture, Bu-Ali Sina University, Hamedan, Iran.

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ABSTRACT: This study investigated the use of an adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithm–artificial neural network (GA-ANN) for the prediction of drying time and moisture content of wild sage seed mucilage (WSSM) in an infrared (IR) dryer. These models (ANFIS and GA-ANN) were fed with three inputs of IR radiation intensity (150, 250, and 375 W), the distance of mucilage from the lamp surface (4, 8, and 12 cm), mucilage thickness (0.5, 1, and 1.5 cm) for prediction of average drying time. Also, to predict the moisture content, these models were fed with 4 inputs IR power, lamp distance, mucilage thickness, and treatment time. The GA–ANN model structure that used 4 hidden neurons, and modeled the drying time of WSSM with a correlation coefficient (r) of 0.984. Also, the GA–ANN model with 9 neurons in one hidden layer, predicts the moisture content with a high r-value (r=0.999). The calculated r-values for the prediction of drying time and moisture content using the ANFIS-based subtractive clustering algorithm were 0.925 and 0.998, respectively, that shows a higher correlation among predicted data and experimental data. Sensitivity analysis results demonstrated that IR intensity and mucilage distance were the main factors for the prediction of drying time and moisture content of WSSM drying, respectively. In summary, the GA–ANN approach performs better than the ANFIS approach and this method can be applied to the relevant IR drying process with satisfactory results.

Keywords: Genetic Algorithm, Infrared Drying, Sensitivity Analysis, Subtractive Clustering.

Introduction

Dried seeds mucilage (hydrocolloids or gums) are hydrophilic molecules and they can be used as functional ingredients in food products formulation for improving food viscosity and consistency, and controlling the microstructure, texture, flavor, and shelf life (Salehi, 2020a). Wild sage seed mucilage (WSSM) is a gum extracted from wild sage (*Salvia macrosiphon* L.) seeds (Salehi, 2017). The physicochemical characteristics, colour and viscosity of seed gums such as WSSM depend on the drying technique and conditions (Amini *et al.*, 2021). Color changes and drying kinetics modeling of

[*]Corresponding Author: F.Salehi@Basu.ac.ir

basil seed mucilage during IR drying process were investigated by Amini *et al.* (2022). The authors reported that the drying time of basil seed mucilage was decreased when the sample distance from the IR lamp was decreased. The results showed that IR drying technique has great industrial potential in saving processing time as well as energy with better maintenance of color and quality of dried basil seed mucilage.

Drying is one of the simply available and most common processing approaches that have been used traditionally for product preservation. One of the best ways to reduce the drying duration is to provide heat by infrared (IR) radiation. IR technique could be used as a substitution for the common drying techniques for manufacturing high-quality dried hydrocolloids. IR drying has many advantages such as: high heat transfer rate, low drying time, high performance (80-90%), lower energy utilization and costs, and better final product quality (Aktaş *et al.*, 2017; Salehi, 2020c). In addition, the use of an IR dryer in combination with other dryers helped to decrease the drying time by raising the drying rate that leads to decreased energy utilization. Also, symmetrical temperature sharing by IR improved the final product quality (Baeghbali *et al.*, 2019). Comparing convective and IR radiation as a means of pomegranate arils drying was studied by Briki *et al.* (2019). The authors reported that the minimum times needed to reach 9% moisture (w/w) starting from 78% were 510 and 94 min for convective and IR drying, respectively. In addition, Łechtańska *et al.* (2015) examined the IR-assisted hot air drying of green pepper. They reported about a 38% decrease in drying time in comparison to the drying by using the hot-air dryer. In another study, the influence of IR treatment on low-humidity hot air drying of apple slices was investigated by Shewale and Hebbar (2017). They observed that pretreatment with IR waves decreased the drying time approximately to 23% and 17% in low-humidity air and hot air drying, respectively.

The performance of artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) were reported by some researchers. They reported that these approaches can estimate the drying kinetics of various fruits and vegetables with high precision. It has been shown that nonlinear approaches based on ANN are far better in generalization and estimation in comparison to empirical models (Salehi, 2020b; Satorabi *et al.*, 2021). Determination of the best number of neurons in hidden layers of ANN models is generally carried out by trial and error. The genetic algorithm (GA) optimization method can be used to overcome this inherent limitation of ANN. Genetic algorithm–artificial neural network (GA-ANN) has a high capability to find the optimum value of a complex objective function, without falling into local optima (Salehi, 2020b).

ANFIS (neuro-fuzzy) include an ANN structure and a fuzzy inference system (FIS) and uses hybrid learning rules that combine gradient descent, backpropagation, and least square algorithms to estimate a set of data. One approach to the derivation of the fuzzy rules base is to use the self-learning features of ANN, to define the membership functions based on input and output data (Salehi, 2020b). The mostly used fuzzy clustering method is the fuzzy subtractive clustering algorithm. In this algorithm, a cluster with a certain degree has each data point, explained by a membership functions level. The quantity of neuron rules for the model obtained by the subtractive clustering technique is very lower than the model obtained by other techniques (grid partition) (Madadlou *et al.*, 2010; Chen, 2013; Keshavarzi *et al.*, 2017; Al-Amoudi *et al.*, 2019).

ANFIS approach was used to predict the drying kinetics of different agricultural products (Salehi, 2020b). For example, Satorabi *et al.* (2021) investigated the effects of polysaccharide coating on the drying kinetics of apricot slices and used GA-ANN and ANFIS models for the prediction of drying time and moisture content of coated apricot slices in an IR dryer. They reported that the both GA-ANN and ANFIS models predictions agreed well with testing data sets and they could be useful for understanding and controlling the factors affecting the drying kinetics of the uncoated and coated apricot slices in the IR dryer. Lertworasirikul (2008) studied the drying kinetics modeling of semi-finished cassava crackers using empirical, ANN, and ANFIS models, and predicted the drying performance. In another study, Ojediran *et al.* (2020) used the ANFIS approach to estimate the drying kinetics of yam slices during drying by a convective hot air dryer. In this study, the experiments were carried out at various drying air temperatures (50-70°C), air velocities (0.5-1.5 m/s), and yam slices thickness (3-9 mm), and the used experimental data were used for modeling and check the advantage of ANFIS approach. The result displayed the efficiency of ANFIS in predicting drying kinetics at every time and condition of drying with a correlation value of 0.98 for the testing data.

Modeling and estimation of the combined influence of IR power, lamp distance, mucilage thickness and treatment time (main and key parameters in IR dryers) on drying kinetics (drying time and moisture content) of food products using conventional models is difficult. Therefore, the target of this study was to examine the effect of IR dryer parameters on drying time and moisture content of WSSM during IR drying and study the efficiency of GA-ANN and ANFIS methods to estimate these parameters.

Materials and Methods

- *Gum extraction*

Wild sage seeds were purchased from a local market in Hamedan, Iran. The cleaned wild sage seeds were firstly soaked in water at the ratio of seed/water 1:20 at 25°C for 20 min (pH≈7). The mucilage extract was separated from the swollen wild sage seeds by passing the seeds through an extractor (M-J-376-N, Nikko Electric Industry Company, Iran). The initial moisture content of WSSM was equal to 99.4% (wet basis). Finally, the obtained WSSM was immediately placed into the IR dryer.

- *IR drying*

The extracted WSSM was poured into a cylindrical aluminum containers and then dried in an IR dryer (IR radiation lamp (NIR), Noor Lamp Company, Iran). The influence of IR radiation power (at three levels 150, 250, and 375 W), a distance of the sample from the lamp (at three levels 4, 8, and 12 cm), mucilage thickness (at three levels 0.5, 1, and 1.5 cm) and time (min) on drying kinetics of WSSM was examined. The weight changes of WSSM were measured by using Lutron GM-300p digital balance (Taiwan, the sensitivity of ±0.01 gr). All measurements were carried out in triplicate order.

- *Modeling*

IR radiation power, the distance of mucilage from the lamp surface, and mucilage thickness (3 inputs) were used as inputs and average drying time values were used as output. Also, to predict the moisture content, IR power, lamp distance, mucilage thickness, and treatment time (4 inputs) were used as inputs and moisture content values were used as output for GA-ANN and ANFIS models. In the present study, 81 data (3(power)× 3(distance)×3(thickness)×3(repeat)) for average drying time and 10206 data (3(power)×3(distance)×3(thickness) ×126 (average time)×3(repeat)) for moisture content were collected from experiments. The experimental data order was first randomized and then total data were randomly separated into 3 sections: training (35%), validating (15%), and testing data (50%). The testing set data were used to the prediction of the trained network performance on unseen data (Amini *et al.*, 2022).

- *GA-ANN Modeling*

Neurosolution software (version 5, NeuroDimension, Inc., USA) was employed for making the GA-ANN model. In the hidden layers and output layer a sigmoid activation function (Eq. 1) was used (due to the highest r-values (Eq. 2) in comparison to the other functions, hyperbolic tangent and a linear). A sigmoid function is a mathematical function having a characteristic "S"-shaped curve or sigmoid curve. A common example of a sigmoid function is the logistic function shown in the first figure and defined by the formula:

$$f(x) = \frac{1}{1+e^{-x}} \qquad (1)$$

The sigmoid activation function (also called logistic function) takes any real value as input and outputs a value in the range (0, 1). Where x is the output value of the neurons.

$$r = \sqrt{1 - \frac{\sum_{i=1}^{N}[O_i - T_i]^2}{\sum_{i=1}^{N}[O_i - T_m]^2}} \qquad (2)$$

Where O_i is the i^{th} actual value, T_i is the i^{th} predicted value, N is the number of data, and T_m is given by:

$$T_m = \frac{\sum_{i=1}^{N} O_i}{N} \qquad (3)$$

The Levenberg–Marquardt (LM) optimization method was applied to network training. The crossover probability and the mutation probability operators were adjusted equal to 0.9 and 0.01, respectively. Also, a sensitivity analysis was carried out to supply the measure of relative significance between the inputs of the ANN model and to show how the model output changed in response to input changes.

- *ANFIS Modeling*

Matlab fuzzy logic toolbox (R2012a) was used in this study to build an ANFIS model for modeling and estimation of drying time and moisture content of WSSM during IR drying. There are two methods to construct the model in this toolbox: grid partition and subtractive clustering. In the subtractive clustering method, the membership functions are obtained automatically after the generation of clusters (Madadlou *et al.*, 2010; Jalal *et al.*, 2020). In this study, the subtractive clustering algorithm was used to establish the type and quantity of membership functions. A hybrid training method (the mixture of least-squares and backpropagation algorithms) was used as a training method for the ANFIS. The ANFIS structure was trained with the range of influence=0.5, squash factor=1.25, accept ratio=0.5 and reject ratio=0.15.

Results and Discussion

- *GA-ANN modeling results*

GA–ANN method alleviates the problem of determining the hidden neurons numbers and structure of the conventional ANN model layers by trial and error. Error-values (MSE, NMSE, and MAE) calculated by optimized GA-ANN model for prediction of drying time and moisture content of WSSM in an IR dryer reported in Table 1. The calculated r-values for the estimation of drying time and moisture content of WSSM during IR drying show a high correlation between estimated and experimental values. The results showed that a satisfactory agreement between the predicted and experimental data could be achieved by using the GA–ANN model. In addition, the estimation performance of the GA-ANN model for unseen data for drying time and moisture content is presented in Figure 1.

GA-ANN models were developed for the estimation of drying time and moisture content of WSSM during IR drying. In this research, the ANN model was trained using a genetic algorithm to find the best network structure. It was found that GA-ANN with 4 neurons in 1 hidden layer could estimate drying time with a high r-value (r=0.984). The results of the GA-ANN modeling approach showed that this model with 9 neurons in one hidden layer, could predict the moisture content with r-value equal to 0.999.

Table 1. Error values calculated by optimized GA-ANN approach for estimation of drying time and moisture content of wild sage seed mucilage in an infrared dryer

Performance	Drying time	Moisture content
Mean squared error (MSE)	284.158	2.127
Normalized mean squared error (NMSE)	0.058	0.002
Mean absolute error (MAE)	13.216	1.130
Minimum absolute error	0.943	0.001
Maximum absolute error	42.740	6.669
Correlation coefficient (r)	0.984	0.999

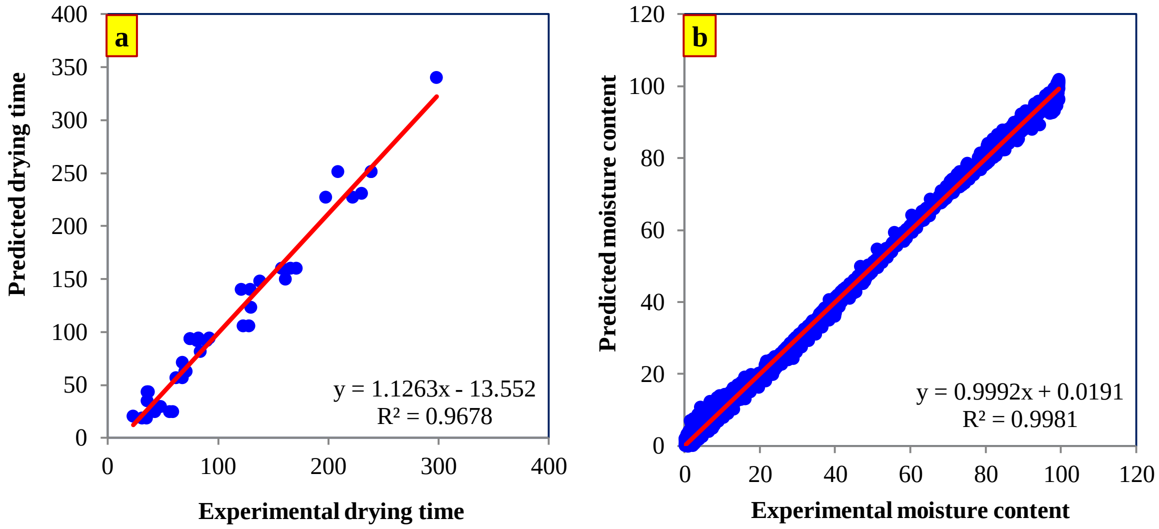

Fig. 1. Experimental versus predicted values of drying time (a) and moisture content (b) using GA–ANN model

Tables 2 and 3 demonstrate the best GA-ANN network weight and bias values for drying time and moisture content changes of WSSM drying, respectively, which could be used in a computer program for the prediction of these parameters.

Sensitivity analysis was used to examine the sensitiveness of GA-ANN structures toward various inputs (Figures 2 and 3). Sensitivity analysis results demonstrated that IR intensity and mucilage distance were the major sensitive inputs for the estimation of drying time and moisture content of WSSM in an IR dryer, respectively.

Table 2. The weight and bias data of the best GA-ANN structure for estimation of drying time

Hidden neurons	Bias	Input neurons			Output neurons
		IR power/W	Distance/cm	Thickness/cm	Drying time/min
1	-6.6432	-6.2751	3.0325	3.3484	8.3696
2	0.5611	2.9699	-1.9598	-3.6307	-2.7283
3	1.1985	-2.1876	-6.4309	-7.0778	-1.9118
4	4.6508	-1.6635	-0.8847	-2.1151	3.9414
Bias					-1.9085

Table 3. The weight and bias data of the best GA-ANN structure for the estimation of moisture content

Hidden neurons	Bias	Input neurons				Output neurons
		Time/min	IR power/W	Distance/cm	Thickness/cm	Moisture content/%
1	-5.7097	-1.2191	7.2111	22.1240	-2.5195	25.9309
2	0.9026	0.3630	-3.0354	1.9858	3.4700	-43.3352
3	-6.6257	-1.3803	11.2644	3.6248	-4.4659	-23.8027
4	1.1874	28.8342	0.0534	0.0424	-0.1052	-22.0290
5	2.0919	-3.0660	-3.0660	-1.4558	-0.0983	7.2876
6	-18.7008	-1.6699	9.1758	16.9462	-3.5263	28.5423
7	1.6354	-1.9451	-2.2335	1.4967	2.5281	85.0715
8	-6.8618	2.5882	-10.1558	22.2612	3.2949	-25.6500
9	-5.2855	-11.3173	5.4619	-6.0564	-2.0229	56.3782
Bias						-2.1882

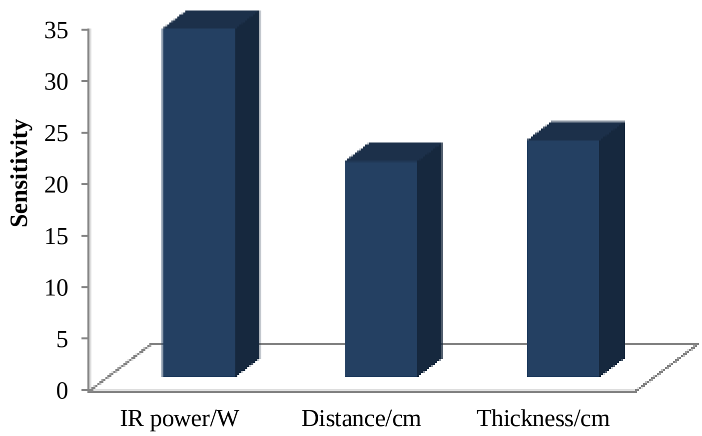

Fig. 2. Sensitivity analysis results for drying time data of wild sage seed mucilage.

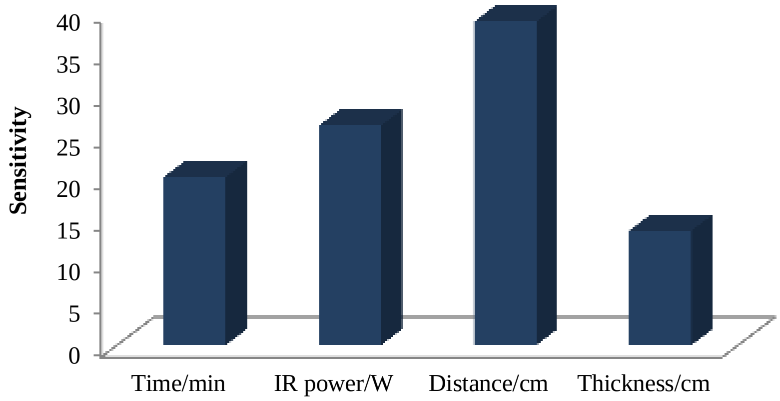

Fig. 3. Sensitivity analysis results for moisture content of wild sage seed mucilage.

- *ANFIS modeling results*

The ANFIS network was trained with 100 observations that were used to build the model. Finally, the ANFIS structure for estimating the drying time of WSSM, with 20 Gaussian type membership functions for 3 inputs and linear membership function for output, and the creation of 20 rules resulted in good accurate estimation (Figure 4). The drying time of WSSM in an IR dryer depends on many factors including, IR power, lamp distance, and mucilage thickness. 3-dimensional plots of drying time values versus these parameters were illustrated in Figures 4 (a), (b), and (c). Figure 4 (a) demonstrates the total system response surface for IR power and mucilage distance, Figure 4 (b) shows the surface for IR power and mucilage thickness and Figure 4 (c) shows the surface for mucilage distance and mucilage thickness versus drying time. From Figure 4 (a), (b), and (c), it was observed that there is the nonlinear relationship between the input parameters and drying time and the relationship of parameters was complex.

It was determined that 20 Gaussian membership functions for every input would be adequate to attain the optimum network. Figures 4 (D), (E), and (F) depicts the Gaussian membership functions of the factors; IR power, mucilage distance and mucilage thickness, respectively. These are fine-tuned membership functions used for the linguistic term sets as “low, average, high” of the input parameters, IR power, lamp distance, and, mucilage thickness. As shown in Figure 4 (G), the best Sugeno fuzzy model was get when the rules are equal to 20. The reasoning procedure demonstrates that the drying time of WSSM would be equal to 80 min if the input parameters, IR power, mucilage distance, and mucilage thickness were equal to 263W, 8 cm and 1 cm, respectively. The designed ANFIS structure for the moisture content changes of WSSM in an IR dryer comprised four nodes in input layer (IR power, mucilage distance, mucilage thickness, and treatment time), 99 nodes in the hidden layer and one node (moisture content) in the output layer. Also, the optimal combination of the ANFIS model was acquired when the number of rules is equal to 33. Amini *et al.* (2021) used GA-ANN and ANFIS models for prediction of drying time and moisture ratio of basil seed mucilage during drying by an IR dryer. They reported that the GA–ANN model with 10 neurons in 1 hidden layer could predict the moisture ratio with a high r value (r=0.99). Also, the calculated r values for the prediction of drying time and moisture ratio using the ANFIS-based subtractive clustering algorithm were 0.96 and 0.99, respectively.

In Figures 5 and 6, the drying time and moisture content values versus ANFIS estimation for unseen data (test data) points are shown. The calculated r-values for the estimation of drying time and moisture content were 0.925 and 0.998, respectively, which shows a higher correlation between predicted and experimental values. Generally, these models simply explain the very non-linear process including IR drying. Rahman *et al.* (2012) modeled the effect of thermal conductivity of different fruits and vegetables by multivariable regression, ANN, and neuro-fuzzy models. Between these, the ANFIS approach estimated the conductivity values closer to the experimental data by providing the lowest errors.

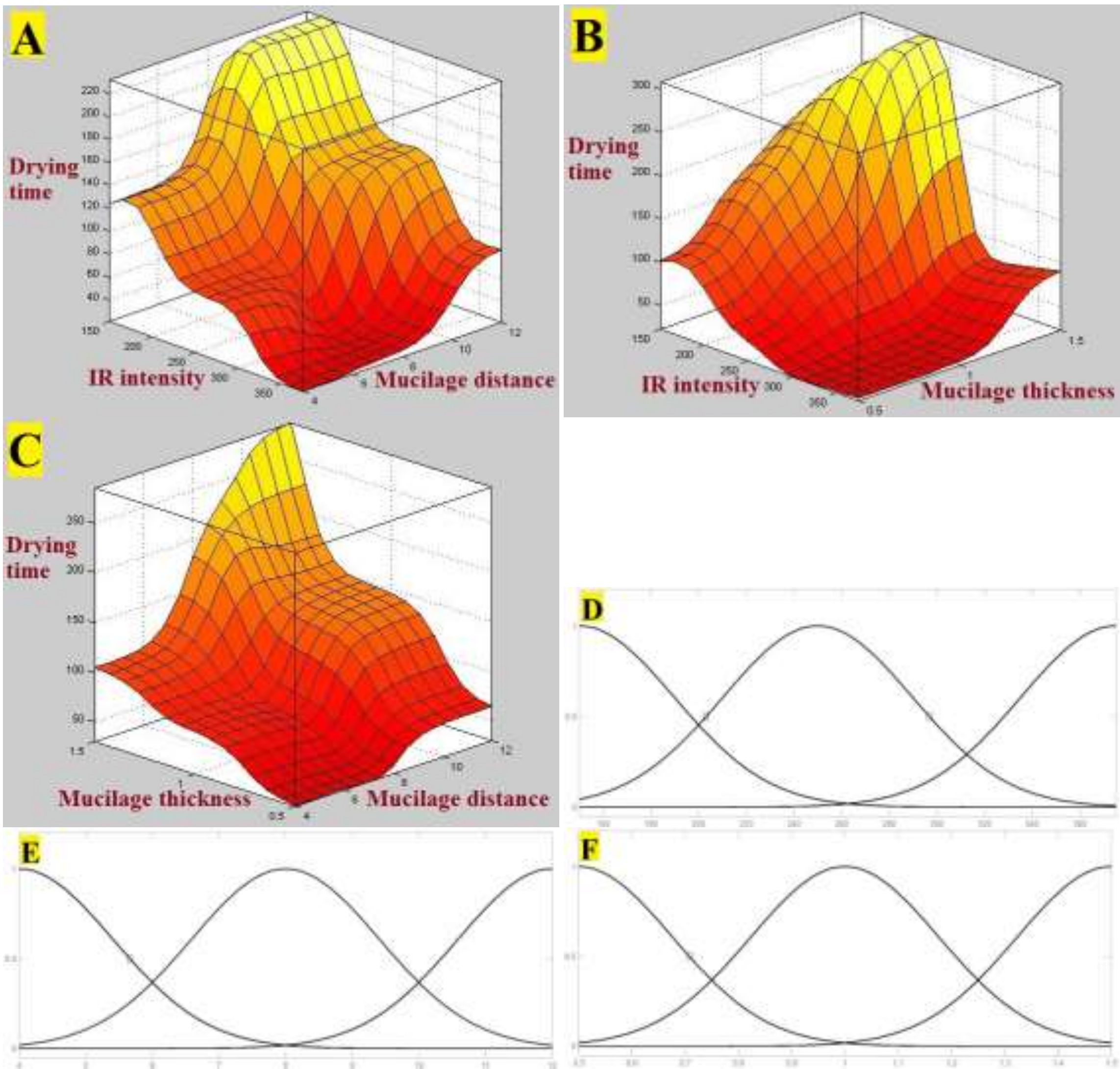

Fig. 4. Response surface diagram for (a) IR power & mucilage distance, (b) IR power & mucilage thickness and (c) mucilage distance & mucilage thickness versus drying time. (D), (E) and (F) the membership functions of IR power, mucilage distance and mucilage thickness, respectively.

Continued Fig. 4.

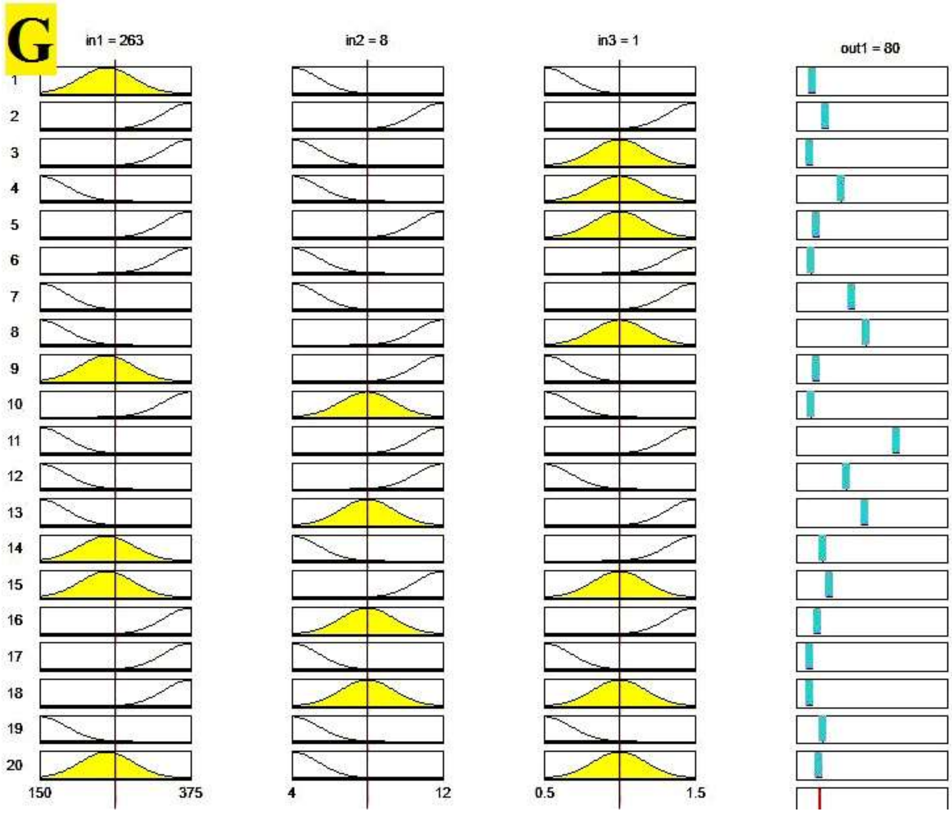

Fig. 4. (Continued) Response surface diagram for (a) IR power & mucilage distance, (b) IR power & mucilage thickness and (c) mucilage distance & mucilage thickness versus drying time. (D), (E) and (F) the membership functions of IR power, mucilage distance and mucilage thickness, respectively. (G) fuzzy process for prediction of drying time.

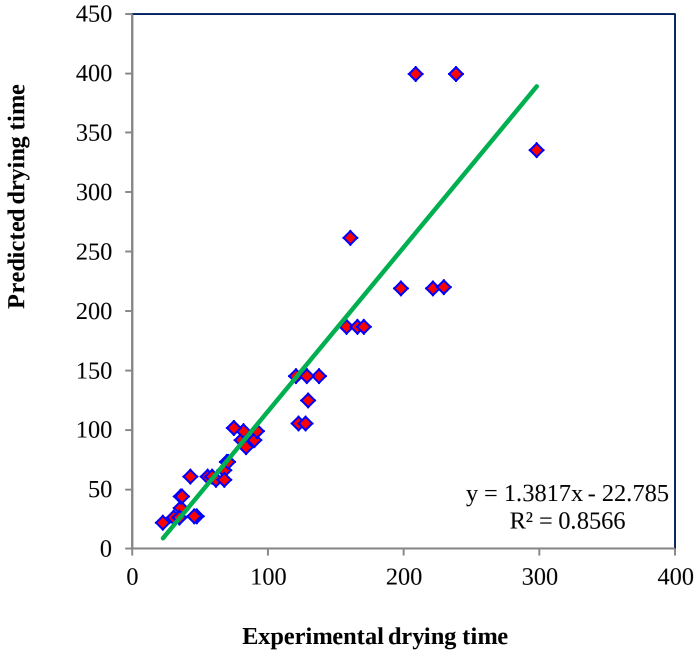

Fig. 5. Experimental versus predicted values of drying time using the ANFIS model.

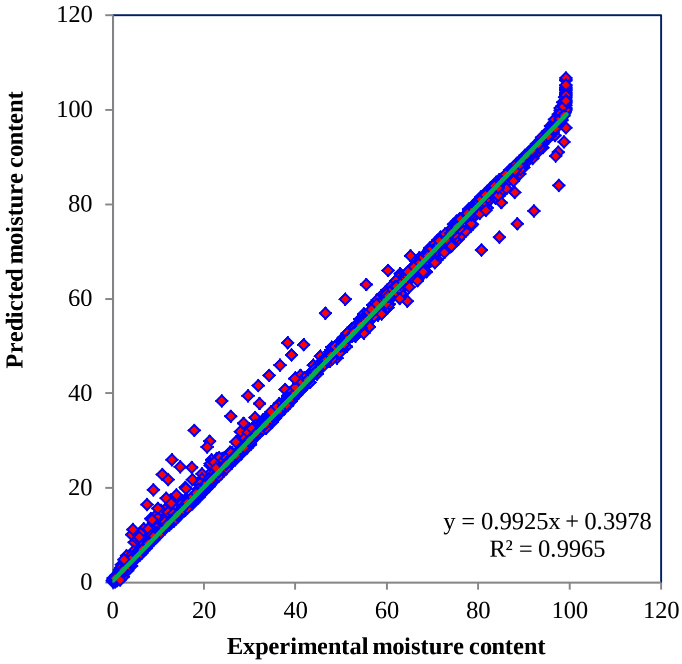

Fig. 6. Experimental versus predicted values of moisture content using the ANFIS model

Conclusion

In this study, the influence of IR drying parameters, including radiation power, the distance of mucilage from the IR lamp, mucilage thickness on drying time, and moisture content of WSSM were studied. Also, the use of GA-ANN and ANFIS methods for the estimation of these parameters was investigated. It was found that the GA-ANN with one hidden layer using 4 neurons gives the best ANN structure that can predict the drying time of WSSM with an acceptable r-value (0.984). Also, to predict the moisture content, these models were fed with four inputs of IR power, lamp distance, mucilage thickness and treatment time and the GA–ANN model with 9 neurons in one hidden layer, estimate the moisture content with high r-value (r=0.999). According to the performance indicators of ANFIS and GA–ANN models, the GA–ANN approach is more accurate in predicting IR drying kinetics of WSSM (drying time and moisture content data) than the ANFIS approach.

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