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MODELING THE DRYING KINETICS OF GREEN BELL PEPPER IN A HEAT PUMP ASSISTED FLUIDIZED BED DRYER

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ABSTRACT

In this research, green bell pepper was dried in a pilot plant fluidized bed dryer equipped with a heat pump humidifier using three temperatures of 40, 50 and 60C and two airflow velocities of 2 and 3 m/s in constant air moisture. Three modeling methods including nonlinear regression technique, Fuzzy Logic and Artificial Neural Networks were applied to investigate drying kinetics for the sample. Among the mathematical models, Midilli model with $R = 0.9998$ and root mean square error (RMSE) = 0.00451 showed the best fit with experimental data. Feed-Forward-Back-Propagation network with Levenberg–Marquardt training algorithm, hyperbolic tangent sigmoid transfer function, training cycle of 1,000 epoch and 2-5-1 topology, deserving $R = 0.99828$ and mean square error (MSE) = 5.5E-05, was determined as the best neural model. Overall, Neural Networks method was much more precise than two other methods in prediction of drying kinetics and control of drying parameters for green bell pepper.

PRACTICAL APPLICATIONS

This article deals with different modeling approaches and their effectiveness and accuracy for predicting changes in the moisture ratio of green bell pepper enduring fluidized bed drying, which is one of the most concerning issues in food factories involved in drying fruits and vegetables. This research indicates that although efficiency of mathematical modeling, Fuzzy Logic controls and Artificial Neural Networks (ANNs) were all acceptable, the modern prediction methods of Fuzzy Logic and especially ANNs were more productive and precise. Besides, this report compares our findings with previous ones carried out with the view of predicting moisture quotients of other food crops during miscellaneous drying procedures.

INTRODUCTION

Fluidized bed drying is a novel and efficient method which makes it feasible to dry food products in continuous and moderate conditions. High rate of heat transfer makes drying a thrifty process; on the other hand, no need for various mechanical parts for drying reduces maintaining costs (Wan Daud 2008). It is very difficult to develop a complete mathematical model for predicting dependent variables of a process considering all independent variables. So far, various modeling methods have been applied to forecast drying kinetics of food products in fluidized bed dryers, although their precision and accuracy for predicting moisture losses in different periods of drying processes are dissimilar (Ratti 2009).

A common technique for determination of moisture loss during drying processes is empirical model; at first, various parameters are measured through lab experiments and then, the best algebraic equation for prediction of variables is selected on the basis of fitting lab data with famous algebraic equations. To date, several scientific articles have been published on regression modeling of drying kinetics for various food products e.g., Mota *et al.* (2010) on onion slices, Ethman Kan *et al.* (2009) on mint leaves, Doymaz

TABLE 1. DIFFERENT STUDIES ON PREDICTING DRYING BEHAVIOR OF VARIOUS FOOD PRODUCTS BY GA AND ANNs

Food product	Drying method	Modeling technique	Result	Reference
Rice paddy	Fluidized bed	GA	Efficient to determine the optimal conditions of drying method	(Atthajariyakul and Leephakpreeda 2006)
Mango	Convective	GA	Better results than empirical and theoretical models	(Vaquiro *et al.* 2008)
Corn malt	Convective	GA	GA suggested 54C and 6 h as the optimum condition	(Curvelo Santana *et al.* 2010)
Sezame	Fluidized bed	GA	GA was successfully applied for improving RSM	(Hashemi Shahraki *et al.* 2014)
Kiwifruit	Osmo-convective	GA and ANNs	GA was successfully applied for optimization of the ANNs' parameters	(Fathi *et al.* 2011)
Carrot	Convective	GA and ANNs	RSM and GA were successfully applied to find the optimum topology of ANNs	(Aghbashlo *et al.* 2011)
Blueberries	Osmo-convective	ANNs	Much better performance than mathematical models	(Chen *et al.* 2001)
Grains	Intermittent	ANNs	High performance in terms of various statistical indices	(Jumah and Mujumdar 2005)
Turnip seeds	Vibro-Fluidized bed	ANNs	High fitting rates were achieved	(Alvarez *et al.* 2005)
Tomato	Tray	ANNs	More accurate than mathematical equations	(Movagharnejad and Nikzad 2007)
Pomegranate juice	Spray	ANNs	3-10-8-5 topology was the best one	(Youssefi *et al.* 2009)
Paddy	Fluidized bed	ANNs	7-13-7-1 topology was the best one	(Chichan Amiri *et al.* 2009)
Grains	Fixed bed	ANNs	Successful to determine the moisture distribution	(Farkas 2013)
Carrot	Fluidized bed	ANNs	Training and validation stages of ANNs had a strong influence on its applicability	(Nzaghelichi *et al.* 2011)
Canola	Fluidized bed	ANNs	Much better performance than mathematical models	(Malekjani *et al.* 2013)

ANNs, artificial neural networks; GA, genetic algorithms.

(2004) on carrot slices and Di Scala and Crapiste (2008) on red pepper.

Nowadays, due to fast development of computer technologies, creation of related software and invention of artificial intelligent technologies including Fuzzy Logic and Artificial Neural Networks (ANNs), it is being made possible to solve complicated problems in relation to systems or process modeling.

Genetic algorithm (GA) is one of the optimization techniques to reach an optimal value of a complex objective function by simulation of biological evolutionary processes based on crossover and mutation (Erenturk and Erenturk 2007). Earlier research have demonstrated that the results for application of various drying methods, mainly convective methods, on different products could be forecasted by GA (Table 1).

Fuzzy Logic is based on fuzzy set theories. This theory has been generalized from classic theories of collections (in mathematics) and functions on the basis of numeral calculations upon created amounts (for each fuzzy variable) by a membership function. Fuzzy rules and logics are backbones of fuzzy interference models. Mamdani fuzzy model is one of the most important modeling tools on the basis of fuzzy set theories (McNeill and Freiberger 1994; Timothy 2010).

ANNs are nonlinear mathematical algorithms and their performance style is similar to the human brain; this technique has been applied for mathematical modeling of independent (input neurons) and dependent (output neurons) variables. The quantity of each hidden neuron is a weighted linear combination of input neurons; output neurons receive an input number from each hidden neuron and transfer function[1] is applied to determine final output quantity. Previous research have proved that application of various drying methods on different products could be predicted very well by ANNs in terms of statistical indices (Table 1).

Fluidized bed dryers are one of the best energy saving dryers. Because there are some constraints for their application on particular and granular materials (e.g., cereals or leguminous), application of these dryers is limited for other crops (e.g., fruits and vegetables). Forecasting kinetics of food drying in these dryers with application of modern modeling techniques including Fuzzy Logic and ANNs, comparison and evaluation of obtained patterns in real conditions seem inevitable to optimize drying conditions and operation costs. The aims of this research were to dry green bell pepper in a custom designed fluidized bed dryer and predict its behavior during drying by three different modeling methods and to compare the accuracy of those models.

[1] Activation function.

MATERIALS AND METHODS

Pilot Plant Fluidized Bed Dryer Apparatus

A pilot plant fluidized bed dryer having closed airflow circulation and equipped with a heat pump dehumidifier system was applied for drying green bell pepper. According to Fig. 1, different parts of the system were fixed in a frame with $170 \times 80 \times 90$ cm^3 dimensions. The system included a vane centrifuge blower (2 hp power) equipped with a frequency inverter (SVO 15IC5, Seoul, Korea) in order to set the intensity of input airflow. The moisture controller system was made of a compressor, a condenser and an evaporator, which could regulate the entrance of moisture within the machinery. The drying chamber was made of Plexiglas and had 20 cm diameter and 60 cm height. On arrival, middle and terminal parts of the machinery, precise sensors of airflow moisture (SIWAN moisture tester, K200, Taipei, Taiwan), temperature (ATBIN digital thermostat, 915055, Tehran, Iran) and velocity were fixed; sensors were equipped with cascade-forward programs and could set conditions if unwanted changes occurred. There were other sensors inside tubes, on conjunction points and after the condenser to control all parts of the machine.

As opposed to current systems which have open airflow circulation and no dehumidifier system, in our designed dryer, waste of energy could be kept at minimal rates and there is no need for such a long time or much energy to heat drying air (Ratti 2009).

Drying Material and Method

Fresh bell peppers were purchased from a local market in Gorgan (Iran). Samples were transported to lab after packaging in nylons and held in the refrigerator. Initial moisture of samples was measured 91.4% (w.b.) using the *Official Methods of Analysis* (Association of Official Analytical Chemists 1999). For each drying treatment, some peppers were taken out from nylons and cut into slices with 10 mm length, 10 mm width and 1.5 mm thickness by a sharp knife after removing their tail and white seeds. An amount of 50 g (on average) of samples was weighed by a digital balance (GK1203, Sartorius Co., Göttingen, Germany), displaced to the feed disk of drying apparatus and dried. During the process, every 10 min, the samples were removed, weighed (to analyze moisture content) and re-dried till there was less than 0.1 g difference between two consecutive weight measurements. In this stage, moisture of samples was measured again and considered as equilibrium moisture. Measured weights were converted to moisture ratios by the following equation

$$\mathrm{MR} = \frac{M - M_e}{M - M_0} \tag{1}$$

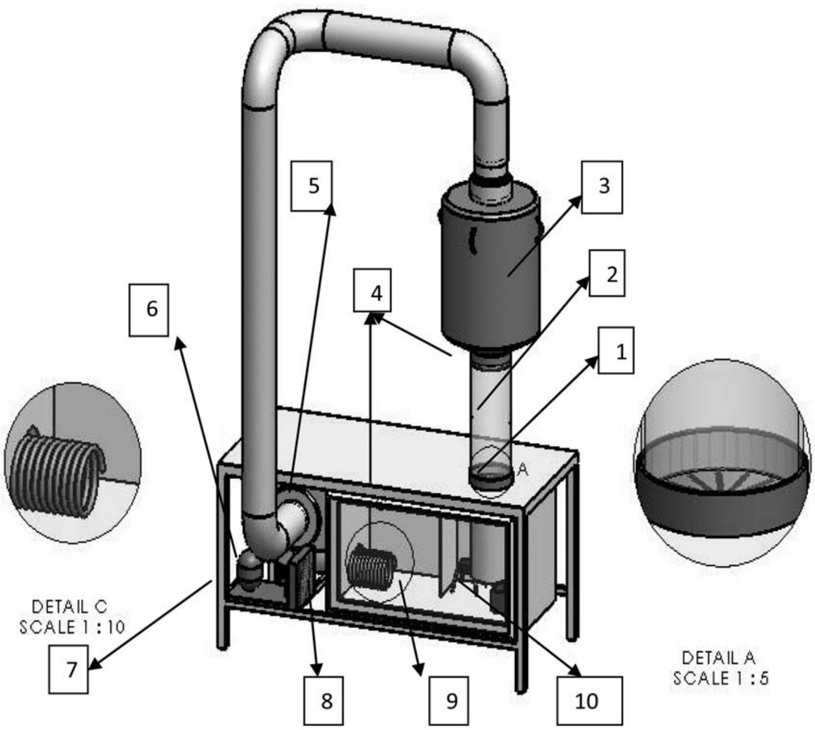

FIG. 1. A PILOT PLANT FLUIDIZED BED DRYER EQUIPPED WITH A MOISTURE CONTROLLER SYSTEM
1. Meshed plate to feed the chamber. 2. Main chamber of fluidization made from Plexiglas. 3. Help chamber of fluidization made from Steel. 4. Sensors for air temperature, relative humidity and velocity. 5. Centrifugal blower. 6. Compressor. 7. Condenser. 8. Evaporator. 9. Heater. 10. Air dispenser plate (having accumulated tubes).

where MR, M, M_0 and M_e were moisture ratio (dimensionless), moisture content (d.b.), initial moisture content (d.b.) and equilibrium moisture content (d.b.), respectively.

Regression Modeling

Curve fitting tool of MATLAB 7.10 (Mathworks, Inc., Natick, MA) and nonlinear regression technique were applied to fit experimental moisture ratio data with predicted ones by mathematical models; constant coefficients and evaluation factors of applied mathematical models were estimated properly. Mathematical models were compared on the basis of three well-known statistical factors including correlation coefficient (R), root mean square error (RMSE) and sum of squares error (SSE). Among the presented models, a model with maximum R and minimum RMSE and SSE was selected as the best model to forecast the drying process. Table 2 represents applied mathematical models.

Modeling with Application of Fuzzy Logic

Simulation of experimental moisture ratio data was carried out with Fuzzy Logic tool in MATLAB and Mamdani method under If–Then fuzzy rules for two input and an output variables. Therefore, moisture ratios after certain periods of time (every 10 min) were simulated on the basis of drying airflow temperature in three levels with fuzzy terms of "low" for temperature of 40C, "medium" for temperature of 50C and "high" for temperature of 60C and drying airflow velocity in two levels with fuzzy terms of "low" for velocity of 2 m/s and "high" for velocity of 3 m/s.

TABLE 2. MATHEMATICAL MODELS APPLIED FOR REGRESSION MODELING OF DRYING KINETICS FOR GREEN BELL PEPPER IN A FLUIDIZED BED DRYER

Model number	Model name	Model equation
1	Newton	MR = exp(–kt)†
2	Logarithmic	MR = a exp(–kt) + c
3	Page	MR = exp(–kt^n)
4	Two-term exponential	MR = a exp(–kt) + (1–a) exp(–kat)
5	Wang and Singh	MR = 1 + at + bt^2
6	Approximation of diffusion	MR = a exp(–kt) + (1–a) exp(–kbt)
7	Modified Henderson and Pabis	MR = a exp(–kt) + b exp(–gt) + c exp(–ht)
8	Midilli–Kucuk	MR = a exp(–kt^n) + bt
9	Henderson and Pabis	MR = a exp(–kt)

† k, g and h are model constants in the units of (min^{-1}) and a, b, c, d, e and f are dimensionless constants of mentioned models.
MR, moisture ratio.

Final moisture ratio was obtained from six applied temperature–time treatments i.e., 40C–2 m/s, 40C–3 m/s, 50C–2 m/s, 50C–3 m/s, 60C–2 m/s and 60C–3 m/s with fuzzy terms of "very high", "high", "medium", "low", "very low" and "very very low" (respectively). Triangular membership functions were applied for setting some changes in three variables i.e., temperature, velocity and moisture ratio. A triangular membership function with three parameters of $\{a, b, c\}$ was defined by following equation (Akpinar 2006)

$$\text{Triangle}(x; a, b.c) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{cases} \tag{2}$$

Interpolation was done by extracting moisture ratios from fuzzy interference and three-dimensional (3D) surface plots for every 1 degree change in the range of 40–60C and for different drying times at two air velocities of 2 and 3 m/s.

Modeling with Application of ANNs

Neural Networks having two neurons for their input layer (time and airflow temperature) and a neuron for output layer (moisture ratio) were designed for two different air velocities of 2 and 3 m/s by applying interpolation results extracted from fuzzy modeling. After trial and error, network unit with Feed-Forward-Back-Propagation structure, hyperbolic tangent sigmoid transfer function for neurons of hidden layer, linear transfer function for neuron of output layer, Levenberg–Marquardt training algorithm on the basis of hessian matrix and training cycle of 1,000 epoch with assistance of two evaluation factors i.e., R and mean square error (MSE), were selected. Besides, through the process, 60% of the data were applied for training, 15% for validation and 25% for test of selected networks. The best topology (with the highest R and the least MSE) was selected for fluidized bed drying process of green bell pepper by changing number of hidden layers and number of neurons for each layer.

Optimum transfer function for each neuron of hidden layers was hyperbolic tangent sigmoid transfer function (Eq. 3) for two consecutive layers of i and j:

$$Y_j = \frac{2}{\left(1 + \exp\left(-2x_j\right)\right)} - 1 \tag{3}$$

Y_i was the output of neuron number j and X_i was the sum of weighted inputs for each neuron of layer number j; the latter parameter was calculated according to Eq. (4):

If (Tem is low) and (Vel is low) then (MR is VH)
If (Tem is low) and (Vel is high) then (MR is H)
If (Tem is medium) and (Vel is low) then (MR is M)
If (Tem is medium) and (Vel is high) then (MR is L)
If (Tem is high) and (Vel is low) then (MR is VL)

FIG. 2. MAMDANI METHOD UNDER SIX IF–THEN FUZZY RULES FOR TWO INPUTS (TEMPERATURE; TEM AND VELOCITY; VEL) AND AN OUTPUT (MOISTURE RATIO; MR) VARIABLE
VH: Very High; H: High; M: Medium; L: Low; VL: Very Low; VVL: Very Very Low.

$$x_j = \sum_{i=1}^{m} w_{ij} \times Y_i + b_j \tag{4}$$

m, w_{ij}, Y_i and b_j were number of neurons for layer j, weight between i and j layers, output of neuron layer i and bias of layer j, respectively. Neurons of input layer did not have a transfer function and neuron of output layer followed linear transfer functions (Bahmani *et al.* 2015).

Experimental Design and Data Analysis

Different treatments were designed for three levels of airflow temperature (40–50–60C), two levels of airflow velocity (2 and 3 m/s) and constant dimensions of sample ($1.5 \times 10 \times 10$ mm) at a completely randomized factorial design with three replications. Data analysis and mean comparison were performed with application of Statistica 9.0 (Statsoft, Tulsa, OK) and Duncan's test in the level of $P < 0.05$, respectively. EXCEL software (Microsoft, New York) was applied for plotting data.

RESULTS AND DISCUSSION

Regression Modeling for Drying Kinetics of Green Bell Pepper

Curves of moisture ratio against time were plotted for different conditions of drying to investigate drying kinetics and mechanisms of moisture transfer (Fig. 2).

By the increase of airflow temperature from 40 to 60C, slope of curve was increased. A similar trend was also observed by the increase of airflow velocity from 2 to 3 m/s; the effect of two parameters on drying rate was statistically significant ($P < 0.05$). Obviously, the effect of velocity was too negligible compared with the effect of temperature. In other words, the most effective factor on the drying rate of green bell pepper was temperature. Akpinar (2006) and Mota *et al.* (2010) reported temperature as the most effective factor on thin-layer drying of some fruits and vegetables, too. Trend of changes in moisture ratio versus time implies that our sample lost the largest part of its moisture in the period of descending velocity and the dominating mechanism of moisture transfer in the drying course was vapor diffusion (Chen and Mujumdar 2008).

Table 3 represents evaluation factors obtained by fitting experimental moisture ratio data with mathematical models. The Midilli model with $R = 0.9999$, $RMSE = 0.00451$ and $SSE = 0.000264$ was the best one to describe drying kinetics for green bell pepper. The Midilli model had also been introduced as the best one to describe drying behavior of some other agricultural crops such as onion and apple slices (Meisamiasl *et al.* 2010; Mota *et al.* 2010). By considering constants and factors of the Midilli model ($a = 0.9985$, $b = -0.0001$, $k = 0.0545$, $n = 0.8591$), the following equation could be successfully applied for predicting the moisture ratio of green bell pepper at different stages of the fluidized bed drying process:

$$MR = 0.9985 \exp\left(-0.0545 t^{0.8591}\right) - 0.0001 \tag{5}$$

In order to evaluate the validity of the selected model (Midilli model), moisture ratio experimental data obtained during the drying process were compared with forecasted ones by the Midilli model (Fig. 3). The points were located on the 45° straight line deserving very a high rate of correlation ($R = 0.999$); therefore, it can be concluded that the Midilli model was suitable for predicting drying kinetics of green bell pepper.

Modeling Drying Kinetics for Green Bell Pepper by Applying Fuzzy Logic

In order to simulate the drying process of green bell pepper, triangular membership function was designed for setting temperature, velocity and moisture ratio changes in periodic times of 10 min by application of Fuzzy Logic tool in MATLAB. Figure 4 represents a sample of membership functions at the 50th min of drying process.

The results of simulating moisture ratio data were depicted in terms of fuzzy interference and 3D surface plots by Fuzzy Logic tool. Figure 5 represents two plots of drying process at the 50th and 100th min.

Fuzzy interference plots give an outline of fuzzy modeling process and indicate effects of each membership function on final results, individually. In the plots, each row and column is related to an If–Then rule and a variable, respectively. For example, regarding the fuzzy interference plots (Fig. 5), moisture ratio of 0.0589 will be obtained at 45C and 2.8 m/s after 100 min of the drying process. In order to evaluate accuracy of interpolation and confirm the obtained fuzzy model, moisture ratio data for treatments with 2 m/s–50C and 3 m/s–50C conditions were extracted from fuzzy interference plots and compared with experimental ones (Fig. 6). High correlation of those data displayed high level of accuracy for selected fuzzy model.

TABLE 3. COMPARISON BETWEEN EXPERIMENTAL AND FITTED MATHEMATICAL MODEL MOISTURE RATIO DATA FOR GREEN BELL PEPPER OBTAINED AT DIFFERENT AIR TEMPERATURES AND VELOCITIES

		Air velocity of 2 m/s			Air velocity of 3 m/s		
Model name	Temperature (C)	SSE	RMSE	R	SSE	RMSE	R
Newton	40	0.015300	0.02380	0.9959	0.008864	0.01883	0.9975
	50	0.013400	0.02526	0.9956	0.004516	0.01680	0.9982
	60	0.001214	0.01006	0.9994	0.001712	0.01370	0.9991
Logarithmic	40	0.036290	0.12300	0.8992	0.005091	0.01488	0.9986
	50	0.008567	0.02123	0.9971	0.003463	0.01573	0.9986
	60	0.001033	0.01016	0.9995	0.001554	0.01490	0.9991
Page	40	0.008761	0.01836	0.9977	0.004465	0.01364	0.9987
	50	0.003220	0.01269	0.9989	0.001407	0.00969	0.9994
	60	0.000834	0.00871	0.9996	0.001220	0.01235	0.9930
Two-term exponential	40	0.013130	0.02248	0.9965	0.002017	0.00917	0.9994
	50	0.001293	0.00848	0.9950	0.002421	0.001271	0.9990
	60	0.000564	0.00716	0.9997	0.001609	0.01418	0.9991
Wang and Singh	40	0.147300	0.07526	0.9604	0.014330	0.07727	0.9592
	50	0.180900	0.09512	0.9367	0.001092	0.00883	0.9995
	60	0.093680	0.09228	0.9561	0.000161	0.00479	0.9998
Approximation of diffusion	40	0.004343	0.01000	0.9988	0.001837	0.00894	0.9995
	50	0.001294	0.00825	0.9995	0.000688	0.00701	0.9997
	60	0.000600	0.00775	0.9997	0.000876	0.01119	0.9995
Modified Henderson and Pabis	40	0.168300	0.08747	0.9546	0.001833	0.00957	0.9995
	50	0.001395	0.00933	0.9995	0.001392	0.01125	0.9994
	60	0.003168	0.02127	0.9985	0.001564	0.01977	0.9991
Midilli–Kucuk	40	0.001201	0.02237	0.9654	0.000773	0.00593	0.9998
	50	0.000447	0.00498	0.9998	0.000264	**0.00451**	**0.9999**
	60	0.001174	0.04397	0.9669	0.000455	0.008708	0.9997
Henderson and Pabis	40	0.009365	0.01898	0.9975	0.005345	0.01492	0.9985
	50	0.008853	0.02104	0.9970	0.003480	0.01523	0.9986
	60	0.001096	0.00998	0.9950	0.001620	0.01423	0.9991

Best fitting conditions are in boldface.
R, correlation coefficient; RMSE, root mean square error; SSE, sum of squares error.

Alvarez-Lopez *et al.* (2005), Vaquiro *et al.* (2008), Perrot *et al.* (2006) and other researchers have mentioned high correlation between the data obtained from Mamdani fuzzy model and measured ones during drying processes of different products.

Modeling Drying Kinetics of Green Bell Pepper by Applying ANNs

Table 4 represents comparison between the effects of hidden layers number and neurons number in each hidden layer on precision of predicting moisture ratios in different times and temperatures of drying at 2 and 3 m/s airflow velocities. Feed-Forward-Back-Propagation network with Levenberg–Marquardt training algorithm, hyperbolic tangent sigmoid transfer function and 2-5-1 topology deserved the maximum R (0.99914) and minimum MSE (0.000054825). Islam *et al.* (2003) reported that one layer topology indicated the best topology for drying tomato slices, too. Generally, Feed-Forward-Back-Propagation neural networks with Levenberg–Marquardt training algorithm and topologies with just one hidden layer have shown to be the best neural models for predicting drying kinetics of different fruits and vegetables.

As weight matrix between input and hidden layer, a hessian matrix was created with connecting two neurons of input layer into five neurons of hidden layer as follows

$$\begin{pmatrix} 4.670 & 9.043 & -1.973 & 2.936 & 1.625 \\ -3.034 & -0.907 & 0.046 & -0.328 & 0.827 \end{pmatrix}$$

As weight matrix between hidden and output layers, a hessian matrix was created with connecting five neurons of hidden layer into a neuron of output layer as shown below

$$\begin{pmatrix} 0.008 \\ 0.035 \\ 4.198 \\ 0.574 \\ -0.504 \end{pmatrix}$$

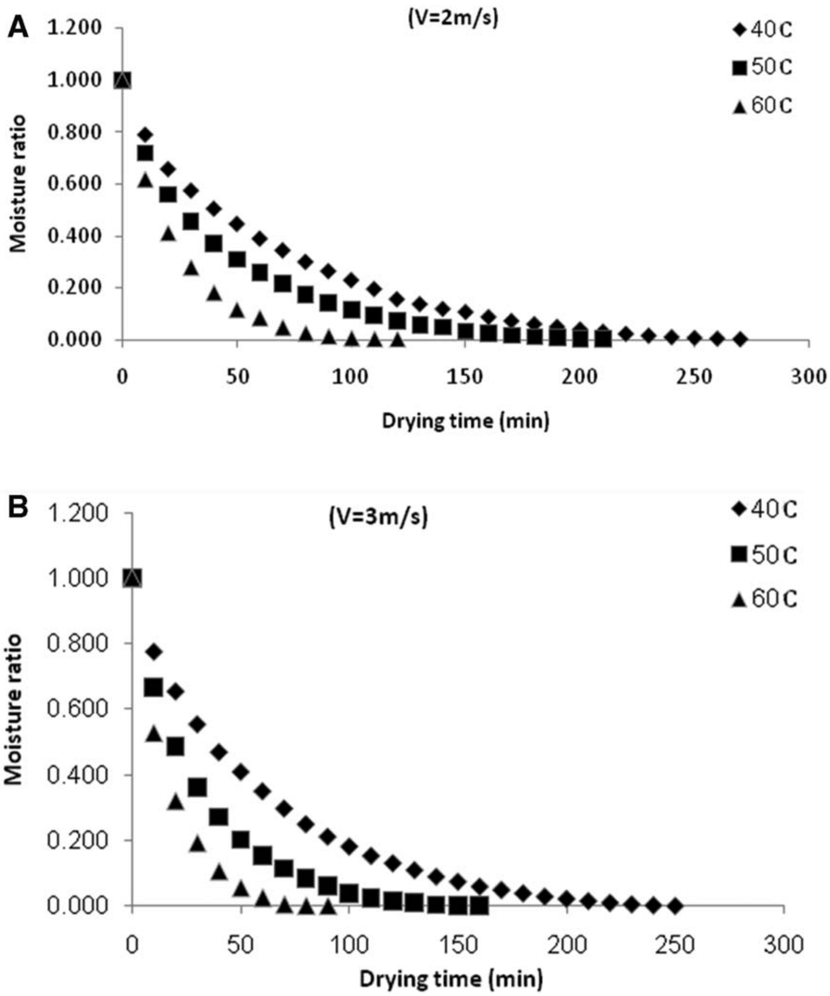

FIG. 3. DRYING CURVES OF GREEN BELL PEPPER AT AIR VELOCITY OF (A) 2 OR (B) 3 M/S AND THREE DIFFERENT AIR TEMPERATURES

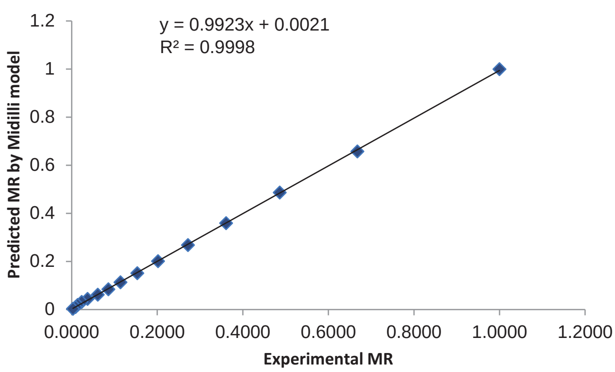

FIG. 4. PREDICTED MOISTURE RATIO DATA BY MIDILLI MODEL VERSUS THE EXPERIMENTAL ONES AT 40C AND 3 M/S AIR VELOCITY

Bias had a format of 5×1 hessian matrix from input layer into hidden layer and 1×1 hessian matrix from hidden layer into output layer:

$$\begin{pmatrix} -2.154 \\ -0.108 \\ -2.628 \\ 2.287 \\ 1.405 \end{pmatrix} \quad (3.806)$$

Hereby, network output (moisture ratio) can be calculated by selection of every arbitrary input (drying time and temperature) for each velocity (2 or 3 m/s).

To validate 2-5-1 topology as the best configuration for modeling bell pepper drying, predicted moisture ratio data were plotted against experimental ones during the whole period of drying process. As it can be seen in Figs. 7 and 8, all points were located near a 45° straight line with a very high correlation coefficient.

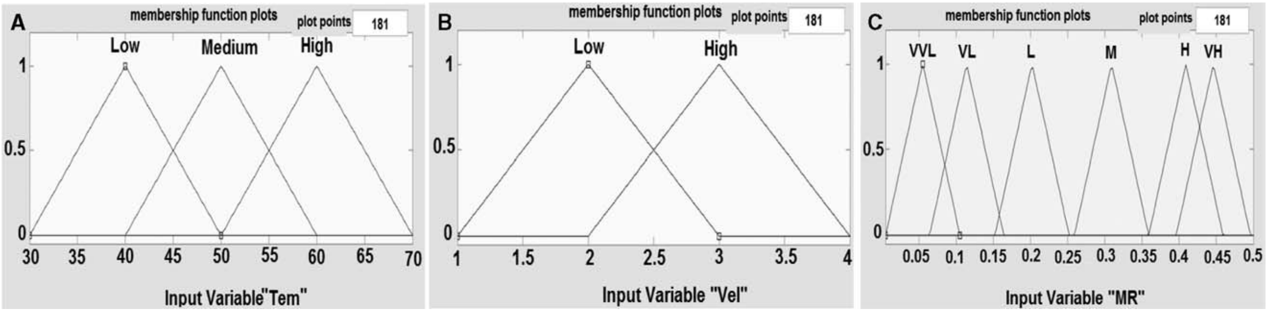

FIG. 5. MEMBERSHIP FUNCTIONS FOR CHANGES IN (A) TEMPERATURE, (B) AIR VELOCITY AND (C) MOISTURE RATIO AT 50TH MINUTE OF DRYING PROCESS FOR GREEN BELL PEPPER

Comparison of Three Modeling Methods

Regression model is a fairly complicated mathematical method, which can just indicate changes in moisture ratios as a function of time on the basis of a series of factors; it can not specify complicated nonlinear relationships between internal and external variables of process. Furthermore, because in this method some series of data fail to get benefit of any training algorithms, the system is not capable of forecasting engaged processes with high probability. Fuzzy

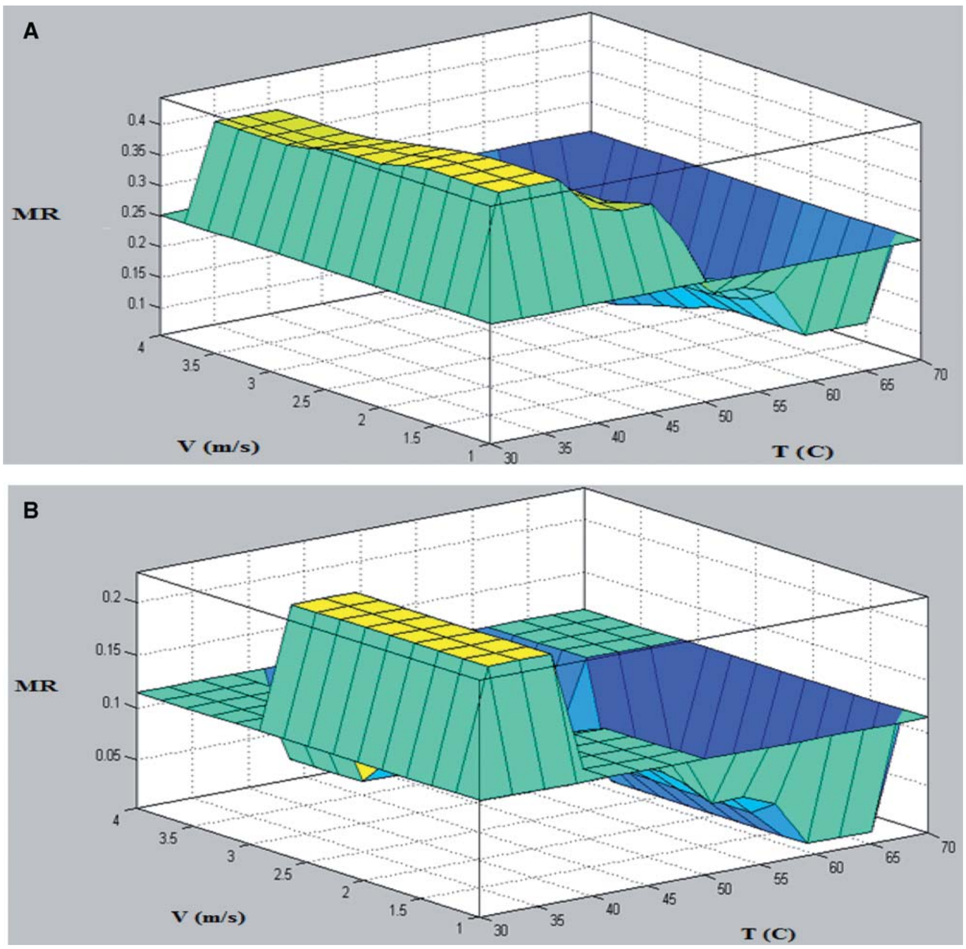

FIG. 6. 3D SURFACE PLOTS INDICATING TEMPERATURE, AIR VELOCITY AND MOISTURE RATIO AT (A) 50TH AND (B) 100TH MINUTES OF DRYING PROCESS FOR GREEN BELL PEPPER

TABLE 4. MONITORING THE EFFECTS OF HIDDEN LAYERS NUMBER AND NODES NUMBER FOR EACH LAYER ON PRECISION OF MOISTURE RATIO PREDICTING AT 2 AND 3 M/S BY ANNs

Number of hidden layer nodes			Air velocity of 2 m/s		Air velocity of 3 m/s	
First	Second	Third	R	MSE	R	MSE
2	–	–	0.99829	0.000088798	0.99856	0.000075693
3	–	–	0.99830	0.000131630	0.99849	0.000052132
4	–	–	0.99899	0.000106180	0.99913	0.000035801
5	–	–	0.99892	0.000073530	**0.99914**	**0.000054825**
6	–	–	0.99907	0.000104780	0.99908	0.000084732
1	1	–	0.98801	0.000615220	0.98372	0.001214900
2	2	–	0.60586	0.022348000	0.99899	0.000034174
3	3	–	0.99904	0.000075920	0.99927	0.000073576
1	2	–	0.98817	0.000805560	0.98416	0.001464500
1	3	–	0.98819	0.000992600	0.98572	0.001420200
2	3	–	0.99854	0.000135900	0.99804	0.000104900
1	1	1	0.98805	0.001028300	0.98349	0.001631900
2	2	2	0.98729	0.001176300	0.03883	0.040755000
3	3	3	0.99922	0.000074330	0.99338	0.000437580
1	1	2	0.98756	0.000984660	0.98433	0.001688100
1	1	3	0.98813	0.001068400	0.98512	0.001567200
1	2	3	0.98709	0.001174000	0.98565	0.000897430
2	2	1	0.044787	0.035521000	0.98518	0.001361600
2	2	3	0.03448	0.036295000	0.03074	0.043841000
3	3	1	0.61505	0.020246000	0.98552	0.000782970
3	3	2	0.99913	0.000067463	0.50310	0.033784000

Best fitting conditions are in boldface.
ANNs, artificial neural networks; R, correlation coefficient; MSE, mean square error.

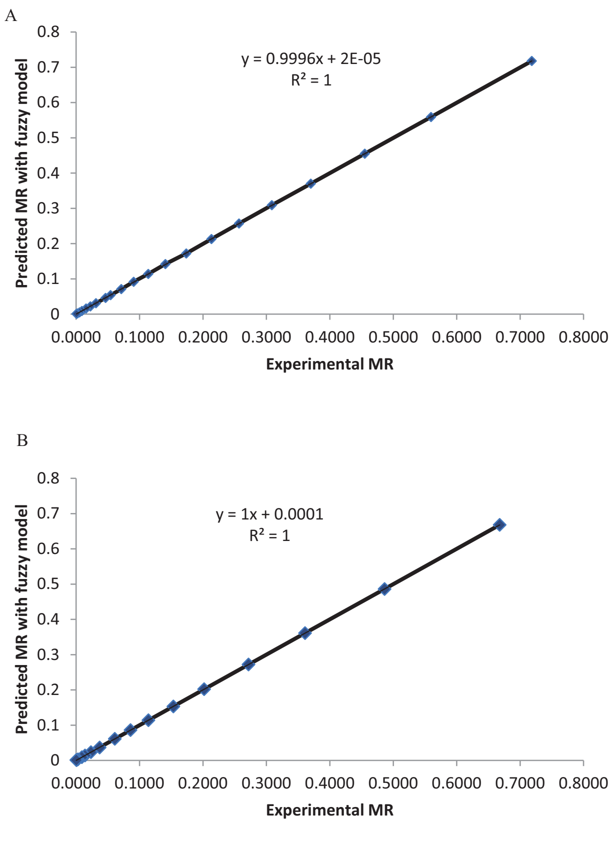

FIG. 7. MOISTURE RATIO DATA PREDICTED BY FUZZY MODEL VERSUS THE EXPERIMENTAL ONES AT 50C AND AIR VELOCITY OF (A) 2 M/S OR (B) 3M/S FOR GREEN BELL PEPPER

model can relate internal and external variables of processes with application of fuzzy interferences and 3D surface plots on the basis of If–Then rules; this model is stronger than empirical models of training aspect, but it has not enough efficiency to predict moisture ratio data relating temperature and velocity extent out of predefined ranges. In other words, fuzzy system is a useful technique for interpolation and to increase experimental data for final application in more complicated modeling methods e.g., ANNs. On the other hand, Neural Network models are not only capable of

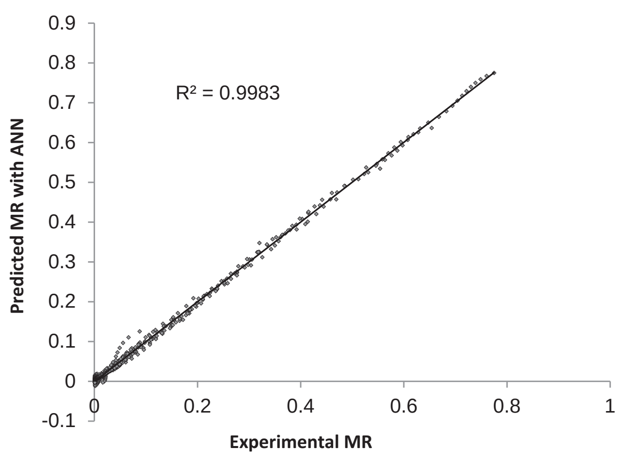

FIG. 8. MOISTURE RATIO DATA PREDICTED BY ANNs AT THE BEST TOPOLOGY (2-5-1) VERSUS THE EXPERIMENTAL ONES DURING FLUIDIZED BED DRYING PROCESS OF GREEN BELL PEPPER

TABLE 5. PREDICTION OF DRYING BEHAVIOR BY ANNs CARRIED OUT ON DIFFERENT FOOD PRODUCTS

Product	Drying method	Input variables	No. of neurons in hidden layers	Output variables	Precision	Reference
Carrot	Convective	4	23	1	RMSE = 0.37	(Aghbashlo *et al.* 2011)
Shelled pistachios	Fixed bed	2	15	1	RMSE = 0.3692 R^2 = 0.99	(Balbay *et al.* 2011)
Pistachio nuts	Thin-layer	3	8	5	RMSE = 4.2E-06 R^2 = 0.9989	(Omid *et al.* 2009)
Alperujo	Fluidized bed	5	6	2	Error less than 10%	(Palancar *et al.* 2001)
Thomson orange	Fluidized bed	2	7	1	RMSE = 0.00012 R^2 = 0.99919	(Sharifi *et al.* 2010)
Onion	Fluidized bed	2	5	1	MSE = 3.9E-05 R^2 = 0.99956	(Ganjeh *et al.* 2013)
Green bell pepper	Fluidized bed	2	5	1	MSE = 5.5E-05 R^2 = 0.99828	Current research

ANNs, artificial neural networks; MSE, mean square error ; R, correlation coefficient; RMSE, root mean square error.

relating internal and external variables, but also able to characterize all possible interactions among internal variables. Neural Network models could be managed to develop by application of multiple training algorithms; moreover, because series of data pass through training, validation and test stages, the R between experimental and forecasted data is increased and MSE is decreased. Previous applications of ANNs for predicting product behavior during drying have led to a high fitting rate for final selected topology (Table 5).

CONCLUSIONS

Three modeling methods including regression technique, Fuzzy Logic and ANNs were appropriate to forecast the drying behavior of green bell pepper during fluidized bed drying. Midilli model could be entitled as a model with the highest performance ($R = 0.9999$, $RMSE = 0.00451$ and $SSE = 0.000264$) among mathematical models to predict moisture ratios at different drying conditions. Very high correlation between the data obtained from Mamdani fuzzy model and experimental ones during drying processes displayed high level of accuracy in selecting fuzzy model. The interpolation results of fuzzy model, having maximum correlation with experimental data ($R = 1$) among three modeling methods, could be used to increase moisture ratio data theoretically and train Neural Networks. A Neural Network with Feed-Forward-Back-Propagation structure, Levenberg–Marquardt training algorithm, hyperbolic tangent sigmoid transfer function and topology of 2-5-1, by a correlation coefficient of 0.99914 and a MSE of 0.000054825, deserved the highest fidelity among different applied topologies and all other models to forecast drying kinetics of green bell pepper.

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