International Food Research Journal 22(3): 1234-1239 (2015)
Journal homepage: http://www.ifrj.upm.edu.my

Modeling for drying kinetics of papaya fruit using fuzzy logic table look-up scheme

[1]Khodabakhsh Aghdam, S.H., [2*]Yousefi, A. R., [3]Mohebbi, M., [3]Razavi, S.M.A., [4]Orooji, A. and [4]Akbarzadeh-Totonchi, M. R..

[1]*Department of Chemical Engineering, Sahand University of Technology, Tabriz, Iran*
[2]*Department of Engineering, University of Bonab, Bonab, Iran*
[3]*Department of Food Science and Technology, Ferdowsi University of Mashhad (FUM), Mashhad, Iran*
[4]*Department of Electrical Engineering, Ferdowsi University of Mashhad (FUM), Mashhad, Iran*

Article history

Received: 17 June 2014
Received in revised form: 17 September 2014
Accepted: 25 September 2014

Keywords

Fuzzy inference system
Modeling
Effective diffusivity
Activation energy

Abstract

Drying kinetics of papaya fruit slices at 40, 50 and 60°C were investigated in a laboratory cabinet dryer. A fuzzy logic table look-up scheme consists of three input variables with 10, 5 and 4 fuzzy sets as well as one output consisting 21 fuzzy sets was designed and used to model the drying kinetics. Mamdani's fuzzy inference system (FIS) with 56 independent rules was used to conduct fuzzy set operations. It was found that the drying process occurred in a falling rate over the drying duration. The effective diffusivity of papaya 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 32.5 kJ/mol, indicated the effect of temperature on the diffusivity. The high values of R^2 (0.977-0.999) in addition with the low values of RMSE (0.013-0.065) obtained for the designed FIS, indicated the high performance of fuzzy logic table look-up scheme to model the drying kinetics of thin-layer papaya slices.

Introduction

Papaya also called Papaw or Pawpaw is an edible melon-like fruit of tropical and subtropical lands. It is juicy and sweet with taste like as cantaloupe (Morton, 1987). Due to high content of vitamin C, K^+, carotenoid and fibers, it has been ranked at the top of fruits (Liebman, 1992). Papaya fruit is widely produced in some countries such as Brazil, Nigeria, India, Mexico and Indonesia. According to the FAO reports, about 6.5 million tons papaya were produced in 2005 (Fernandes *et al*., 2008). In Iran, papaya is grown in Bahowkalat City, Balowchestan province. In 2005, only 480 tones papaya were produced in Iran.

Drying is one of the main operations in the processing chain for reducing spoilage of the agricultural products, especially for susceptible crops such as papaya. Drying process controls enzymatic and microbial activities within the fruits by reducing their water content. Furthermore, the dried fruits occupy less space and are more easily handled (Izadifar and Mowla, 2003). In characterizing drying parameters, thin layer drying procedure was found to be the most feasible tool. There are three types of thin-layer drying model namely: theoretical, semi-theoretical and empirical models (Demirats *et al*., 1998; Midilli *et al*., 2002). The theoretical model depends on physical characteristics of grains. The empirical model neglects the fundamentals of drying process and presents a direct relationship between average moisture and drying time by means of regression analysis (Ozdemir and Devres, 1999). Semi-theoretical is a tradeoff between the theoretical and empirical models, and is derived from Fick s second law of diffusion and is used in the form of the Page model, Modified Page model, Henderson model and others. Kingsly and Singh (2007) studied thin-layer drying process of pomegranate arils at three different drying temperatures (50, 55 and 60°C) in a cabinet dryer and found that the data followed the Page model at all the three temperatures.

Nowadays, artificial intelligent method has been developed and is extensively used for simulation of drying of agricultural and food materials (Tripathy and Kumar, 2009). Zadeh introduced fuzzy sets in 1965 to show a control data and information that possess non-statistical uncertainty (Zadeh, 1965). Fuzzy modeling is the most important issue around fuzzy theory. The fuzzy set is considered as a fuzzy model of a human concept. Indeed, fuzzy modeling system is a linguistic modeling scheme described

*Corresponding author.
Email: karbalaeealiyousefi@gmail.com
Tel: +989178815578

with fuzzy quantities. These fuzzy quantities are expressed through fuzzy numbers or fuzzy sets associated with linguistic sign (Wang, 1997). Ioannou *et al.* (2004) developed a control system based on the fuzzy set theory to measure the product browning. Their model developed using Takagi-Sugeno method. Atthajariyakul and Leephakpreeda (2006) used adaptive fuzzy logic control for systematic determination of optimal conditions for fluidized bed paddy drying in order to guarantee good quality and consume energy efficiency. They concluded that the used method can be efficiently implemented in the real-time determination and control the optimal conditions for fluidized bed paddy drying system. Lertworasirikul (2008) investigated a comparative study on drying kinetics of semi-finished cassava crackers using empirical models, MFNN (Multilayer Feed forward Neural Network) and ANFIS (Adaptive-Network-based Fuzzy Inference System). It was found that among these models, MFNN was the most suitable for predicting moisture ratio of the product based on R^2 and MSE statistical parameters. Zhenfeng *et al.* (2010 a, b) used fuzzy logic systems to improve microwave drying of apple and carrot in terms of volatiles control. Yousefi *et al.*, (2012) compared two modeling methods of mathematical and ANN (Artificial neural networks) to estimate moisture content of papaya fruit slices during hot air drying. They found that estimation of moisture content of papaya fruit could be better modelled 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).

In this study drying kinetics on papaya was investigated. To estimate the moisture content of papaya fruit slices (with 3, 5 and 7 mm thickness) during hot-air drying process at selected temperatures (40, 50 and 60°C), type-1 fuzzy logic modeling system based on table look-up scheme was conducted and the performance of that was evaluated based on the R^2 and RMSE statistical parameters. In addition, effective moisture diffusivity and activation energy of papaya fruit slices were calculated.

Materials and Methods

Experimental study

Papaya fruits were purchased from a local market of Bahookalat region and stored in a refrigerator at 4±1°C prior to subjecting them to the drying process. Fruits were washed, peeled and cut into slices with different thicknesses of 3, 5 and 7 mm. A cabinet dryer (Model JE10 TECH, F-02G, South Korea) with controllable airflow, temperature and air humidity monitoring systems was used for hot air-drying process. The absolute humidity and the hot-air flow ratio for all drying temperatures were 0.6 ± 0.02 g/kg dry air and 1.0 m/s, respectively. The initial moisture content of papaya slices was measured using a laboratory oven dryer (Galenkamp, UK) operating at 105°C, obtained 84.48% ± 0.05% (w. b.). The weight of the samples was consecutively recorded by a programmable balance software in 5 min intervals until the moisture content of the samples reached to 15 ± 0.02% (w. b.) in dried product. Drying process was carried out at three levels of temperature (40, 50 and 60°C). Moisture ratio (MR) variations with time were plotted for various conditions. The MR was defined by:

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

Where, M and M_0 are the moisture content and initial moisture content of the samples, respectively. The moisture ratio equation was simplified to M/M_0 as the value of Me (equilibrium moisture content) is relatively small compare to M or M_0 (Akgun and Doymaz, 2005).

Membership functions and fuzzy table look-up scheme

In brief, a fuzzy inference system (FIS) consists of four main parts: fuzzification, fuzzy rules' base, fuzzy output engine and defuzzification. Fuzzification converts a special input data to ranks of membership by a look-up in one or more various membership functions. Instead of completely pertain to a single set, in a fuzzy logic system, partial pertaining of any objects to different subsets is considered. A membership function numerically describes partial pertaining to a set of particular universe, which assumes values between 0 and 1 inclusive (Wang, 1997). Fuzzy membership functions can take several forms, but generally for practical implementations simple linear ones like triangular function are preferable (Tayfur *et al*., 2003).

In this study the fuzzy logic table look-up scheme was used for estimating the papaya fruit moisture content using fuzzy logic toolbox of MATLAB (R2007b). This method was composed of four stages:

1.Definition of fuzzy sets to cover the input and output spaces:

Three inputs consist of drying time, temperature and thickness of the thin-layered papaya slices were divided into 10, 5 and 4 fuzzy sets, respectively. In addition, one output (Moisture ratio=y) consists of 21 fuzzy sets (Figure 1) was considered for designing a fuzzy logic based modelling system.

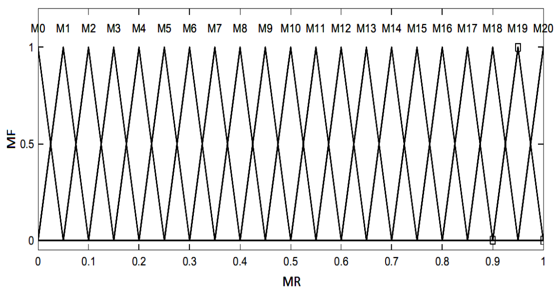

Figure 1. Fuzzy membership functions for output (MR) with 21 fuzzy sets

2.Generation of one fuzzy rule for each of n input-output pair:

Fallowing relation shows input-output pairs by which a fuzzy rule can be generated:

$$(x_1^p, x_2^p, x_3^p, y_1^p) \Rightarrow IF - THEN\ rules \quad p = 1, 2, \ldots, n \qquad (2)$$

Where *X1*, *X2* and *X3* are the input variables and y is output variable and *p* is the number of each input-output pair. To overcome the problem of fuzzy sets overlap, the fuzzy variables were assigned to the membership function with the largest membership value.

3. Calculation of the degree of each rule generated in previous stage:

Due to the large number of input-output pairs, some conflicting rules were generated. In brief, these rules had the same IF parts but different THEN ones. To cope with this conflict, a degree was assigned to each generated rule, so the rule from a conflict group with the maximum degree was selected. Therefore, the conflict problem was resolved and also the number of the initial generated rules reduced. The degree of a rule was defined as follows:

$$D(rule) = \prod_{i=1}^{n} \mu_{A_i^j} * (x_i^p) \mu_{B^l} * (y^p) \qquad (3)$$

Where, A_i^j is the *jth* membership function of the ith input, *B* is rule of output, *l* is the *lth* model output, *p* is index of rule, x_i^p and y^p are the *ith* input of *pth* rule and the *pth* rule of output variables (Wang, 1997).

4.Creation of the fuzzy rule base:

After removing the conflicting rules, the final fuzzy rule base was generated. In this work Mamdani's inference scheme was adopted due to its simplicity. In addition, minimum T-norm operator (Eq. 4) and the center of gravity defuzzifier were used in the fuzzy rule base.

$$T_{min}(a, b) = \min(a, b) = a \wedge b \qquad (4)$$

Where, the *a* and *b* are two optional sets. The center of gravity defuzzifier specifies the y^* as the center of the area covered by membership function of *B'*, that is:

$$y^* = \frac{\int_v y \mu B'(y) dy}{\int_v \mu B'(y) dy} \qquad (5)$$

Where $\int_v$ is a conventional integral (Wang, 1997).

Performance criteria

The performance of the used fuzzy modelling system was evaluated based on the comparison between the predicted MR (from the fuzzy model) and experimental MR using R^2 and RMSE statistical parameters (Eq. 6 and 7). A model with the maximum of R^2 and the minimum of RMSE shows the best performance (Kingsly and Singh, 2007):

$$R^2 = \frac{\sum_{i=1}^{N}(MR_{exp,i} - \overline{MR}_{exp})^2 (MR_{pre,i} - \overline{MR}_{pre})^2}{\sum_{i=1}^{N}(MR_{exp,i} - \overline{MR}_{exp})^2 \sum_{i=1}^{N}(MR_{pre,i} - \overline{MR}_{pre})^2} \qquad (6)$$

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(MR_{exp,i} - MR_{pre,i})^2\right]^{1/2} \qquad (7)$$

Where, $MR_{exp.i}$ is the experimental moisture ratio at observation *i*, $MR_{pre,i}$ is the predicted moisture ratio at this observation, N is number of experimental data points, $\overline{MR}_{exp}$ and $\overline{MR}_{pre}$ are the average of sum of the $MR_{exp.i}$ and $MR_{pre,i}$ respectively.

Results and Discussion

Drying characteristics

Variation of MR with respect to drying time for the three thicknesses and three temperatures are shown in Figure 2a and Figure 2b, respectively. As the results, increasing the thickness from 3 to 7 mm approximately doubled the drying duration at 60°C drying temperature. The air temperature also had a direct effect on drying rate, as the air temperature increased from 40 to 60°C the drying duration was reduced to 100 min.

It is found that there was no constant rate drying period in the drying kinetics of papaya slices, and all drying process occurred in the falling rate period. This matter indicates that diffusion is the controlling physical mechanism regulating moisture transfer in the sample slices. The similar results were reported by Kaymak-Ertekin (2002) for green and red peppers, Sogi *et al*., (2003) for tomato seeds and Doymaz (2007) for pumpkin.

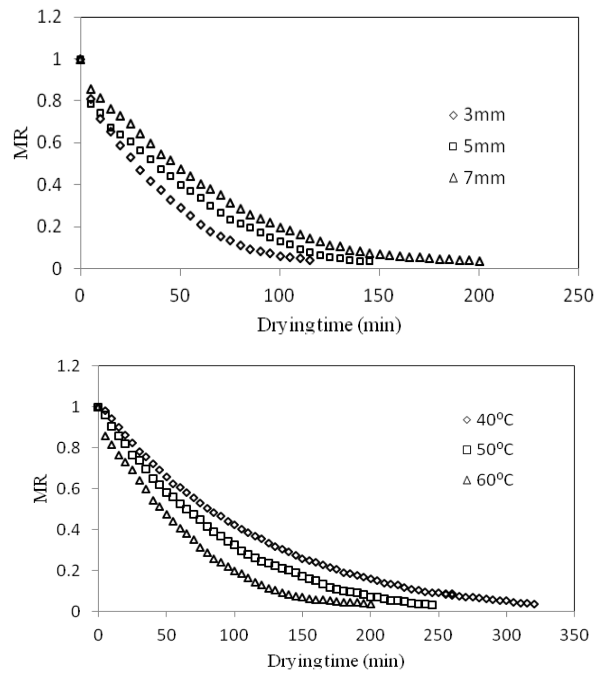

Figure 2. The effect of different (a) thicknesses (at 60°C) and (b) drying temperatures (for the slices with thickness of 7 mm) on moisture ratio

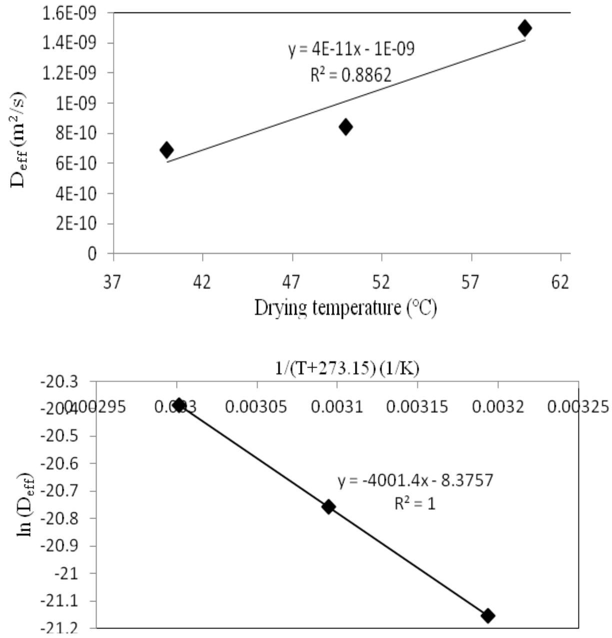

Figure 3. Influence of drying temperature on the (a) effective diffusivity of water in papaya slices and (b) effective diffusivity

Evaluation of the fuzzy logic look-up table scheme drying model

Based on the structure of fuzzy inference system, firstly, by passing the fuzzifier section the fuzzy values are made from the input information by membership functions (Figure 1). Finally, in defuzzification section, obtained fuzzy outputs from the fuzzy inference engine were converted to a number. For drying modelling using FIS, only 15% of the data were used for training or calibrating the system. This training was conducted though 56 rules in which drying time, drying temperature and thickness of the sample slices were related to MR. The antecedent part of the rule (the part starting with IF, up to THEN) included a statement on the drying time, drying temperature and thickness of the sample slices while the consequent part (the part starting with THEN, up to the end) included a statement on MR. It was found that 22 conflicting groups were generated, which by comparison of D (rule) among each group of rules, the rules with the lower D (rule) were removed (Table 1).

At the next stage, through the generated fuzzy rules in the fuzzy rule base, a set of inputs transformed to corresponding set of output. The results of drying modeling at different drying temperature and samples slices based on fuzzy logic table look-up scheme are shown in Table 2. High value of R^2 (0.977-0.999) in addition with the low value obtained for RMSE (0.013-0.065) relating to the experimental and predicted data demonstrated the high performance of the generated fuzzy logic table look-up scheme to determine MR during drying at each temperature and thickness. As the results show, the closest predicted data obtained from FIS to the experimental data was at 60°C-7 mm thickness (R^2=0.999 and RMSE= 0.013) while in contrary the lowest performance attained at 50°C-7 mm thickness (R^2=0.977 and RMSE= 0.065). Yousefi *et al.* (2012) reported that MLP networks could be efficiently used for predicting MR of thin-layer papaya fruit slices (R^2 = 0.9994 and RMSE= 0.0070). It should be noted that although the reported performance for ANN modeling was slightly more than the fuzzy modeling system used in this study, but they used 60% of the data for network training compared to 15% for the fuzzy modeling system. This comparison obviously indicates the remarkable ability of fuzzy modeling system for modeling of drying process. Rahman *et al*. (2012) reported that the adaptive neuro-fuzzy (ANFIS) modeling system can be used to predict the effective of thermal conductivity for various food materials. They demonstrated that ANFIS model could predict that value more closely to the experimental data compared to mathematical and conventional ANN models. Similar results were reported for estimating effective diffusivity using Takagi-Sugeno fuzzy model for mango slices (Vaquiro *et al*., 2008). Ganjeh *et al.* (2013) reported that the combination of fuzzy logic and neural networks is a suitable and reliable method for modeling and prediction of drying kinetics of onion and similar product. Al-Mahasneh

Table 1. Examples of calculated D (rule) to remove inconsistence rules

x1 (Drying time)	*x2* (Drying temp.)	*x3* (Thickness)	*y* (MR)	D (rule)
t1	T1	TH1	M13	0.64 (Removed)
t1	T1	TH1	M12	0.87
t1	T3	TH3	M11	0.75(Removed)
t1	T3	TH3	M13	0.91
t1	T3	TH1	M9	0.63
t1	T3	TH1	M7	0.52 (Removed)

Table 2. The statistical parameters for fuzzy logic based modelling system

Temperature (°C)	Thickness (mm)	R^2	RMSE
40	3	0.997	0.021
	5	0.998	0.014
	7	0.995	0.021
50	3	0.997	0.046
	5	0.996	0.022
	7	0.977	0.065
60	3	0.991	0.038
	5	0.999	0.015
	7	0.999	0.013

et al. (2013) used a fuzzy model to model open sun drying of roasted green wheat. Their results showed a much better performance of fuzzy model compared to conventional models with a much lower value of root mean square error (1.2×10^{-6}).

Calculation of effective diffusivity

From the experimental data, internal mass transfer resistance was observed because of falling rate drying period. Fick's diffusion equation analyzed the drying data in the falling rate period. Crank (1975) solved this equation and introduced the following equation which can be used for slab geometry with uniform initial moisture diffusion, constant diffusivity and insignificant shrinkage:

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

Where, 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 Eq. (8) is used yielding:

$$MR = \frac{8}{\pi^2}\exp\left(-\frac{\pi^2 D_{eff} t}{4L^2}\right) \quad (9)$$

As it is obvious, D_{eff} can be calculated from the slope of Eq. (9) using natural logarithm plot of MR versus drying time. The calculated D_{eff} values for different drying temperatures at 3 mm thickness are shown in Figure 3a. D_{eff} value for papaya slices increased with air temperature. This value was 6.93×10^{-10}, 8.46×10^{-10} and 1.50×10^{-9} m^2/s for 40, 50 and 60°C drying temperatures, respectively. Madamba *et al*. (1996) reported that the D_{eff} value for food materials is within the range of 10^{-11} to 10^{-9}. The obtained results were in agreement with the results of Kaleemullah and Kailappan (2005), Sacilik *et al.* (2006) and Doymaz (2007).

Calculation of activation energy

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

$$D_{eff} = D_0 \exp\left(-\frac{E_a}{R(T+273.15)}\right) \quad (10)$$

Where D_0 is the pre-exponential factor of Arrhenius equation (m^2/s), 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) (Figure 3b). This value was 32.5 (kJ/mol) for papaya slices with 3 mm thickness. This obtained value was lower than the E_a green peppers drying (51.4 kJ/ mol) (Kaymak-Ertekin, 2002), mint drying (82.93 kJ/mol) (Park *et al*., 2002) and higher than red chillies drying (24.47 kJ/ mol) (Kaleemullah and Kailappan, 2005).

Conclusions

In this study, drying kinetics of papaya fruit slices at three drying temperatures and thicknesses in a cabinet dryer were investigated. Like most of food materials, papaya slices had not constant drying rate and drying process entirely occurred in falling rate period. High value of R^2 (0.977-0.999) in addition with the low value obtained for RMSE (0.013-0.065) indicated the high performance of the generated fuzzy logic table look-up scheme to estimate MR during drying at each temperature and thickness. According to the results, fuzzy logic artificial intelligence is a robust system that can be used as an alternative technique to model complex process like drying. The obtained effective diffusivity for papaya fruit slices was within the range of 6.93×10^{-10} to 1.50×10^{-9} m^2/s over the temperature range. It was found that, effective diffusivity increased with increasing drying temperature. The activation energy for papaya slices with 3 mm thickness was found to be 32.5 kJ/mol using Arrhenius equation type.

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