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Artificial Intelligence and Mathematical Modelling of the Drying Kinetics of Pre-treated Whole Apricots

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Abstract

This study involved monitoring and modelling the drying kinetics of whole apricots pre-treated with solutions of sucrose, NaCl, and sodium bisulphite. The drying was performed in a microwave oven at different power levels (200, 400, and 800 W). Two artificial intelligence models were used for the prediction of drying time (*DT*) and moisture ratio (*MR*): artificial neural network (ANN) and an adaptive neuro-fuzzy inference system (ANFIS). On the other hand, the *MR* prediction was also done with 21 semi-empirical models, one of which we created.

The results showed that the drying time decreased with the increase in microwave oven power for the three treatments. The treatment with NaCl was the most suitable for our work. The correlation coefficients of drying time (0.9992) and moisture ratio (0.9997) of ANN were high compared to the ANFIS model, which were 0.9941 and 0.9995, respectively.

Among twenty semi-empirical models that were simulated, three models were fitted to our study (*Henderson & Papis modified, Henderson & Pabis*, and *Two Terms*). By comparing the three models adapted to our work and the model that we proposed, as well as ANN for *MR* prediction, it was observed that the model that we created was the most appropriate for describing the drying kinetics of NaCl-treated apricot. This solution opens the prospect of using this potential model to simulate fruit and vegetable drying kinetics in the future.

Keywords

Apricot, drying kinetics, microwave, models, ANN, ANFIS

1 Introduction

Apricot is the fruit of the common apricot tree, *Prunus armeniaca* L., of the *Rosaceae* family (subfamily *Pomoides*).[1] In 2019, Algerian apricot production amounted to 256.890 tons.[2] For most fresh produce, high humidity over a very short time is one of the most critical factors that affect their physical, chemical, and nutritional quality after harvesting. Therefore, for their consumption, they must be appropriately stored. Several industrial technologies are used in the industry to preserve fruits and vegetables. The most important methods include canning, freezing, deep-freezing, and drying. The drying technique is a very old process for preserving agricultural and food products. Several methods based on air drying, vacuum drying, solar drying, and microwave drying have been used to date for drying fruits and vegetables. Microwave drying method belongs to the type of boiler drying and obeys heat transfer by radiation. Before microwave drying, fruits and vegetables are generally subjected to different pre-treatments, such as blanching, osmotic dehydration in sucrose and salty solutions, and immersion in a sodium bisulphite solution. These treatment methods are commonly used to reduce the rate of fruit browning during drying and storage. They play a critical role in stabilising carotenes, preserving colour, and delaying the product of Maillard reactions. Several researches have focused on the drying of halved apricots and thin layers of apricots treated in solutions (sucrose and sulphide) or untreated. However, to the best of our knowledge, there are no investigations on the effect of dipping the whole apricot in NaCl, sucrose, and sodium bisulphite solutions. Investigations of drying behaviour and kinetics data modelling are reported in the literature for eggplant[3], banana[4], apricot[5], quince[6], potato[7], cranberry[8], apple[9], and beetroot slices[10]. Today, artificial intelligence is also used to solve problems related to process modelling. Artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) models are machine learning-based methods, which apply knowledge to predict complex system outcomes such as drying technology. ANFIS is a system capable of analysing complicated drying processes using the educational power of neural networks and linguistic fuzzy systems.[11] The importance of prediction of process or property cannot be overemphasized. Since many real life processes or properties investigations can be expensive and time-consuming, modelling and prediction from a small experimental data set is a suitable option to forecast a process or properties.[12] *Amini et al.* used ANFIS to predict the drying time of basil seed mucilage.[13] Using artificial intelligence, a number of

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studies have been reported on the prediction of moisture ratio and drying time for various agricultural products, such as apricot slices,[5] quince,[6] onions,[11] basil seed mucilage,[13] green peas,[14] potatoes,[15] and white mulberry.[16] However, there is still very little data reported on drying time prediction of apricot slices by ANFIS and genetic algorithm-artificial neural network (GA-ANN).[5]

Due to the large-volume production of apricot in Algeria, there are significant losses of this fruit as it is perishable. In order to increase its shelf life, decrease the losses of the harvest, encourage local produce and limit the import of this fruit, apricots are dried in the microwave oven, because of its shorter drying time (seconds), low energy cost, and less loss of nutritional elements. The ANN and ANFIS system are used to predict moisture ratio (*MR*) and drying kinetics, in order to reduce drying time (*DT*) and minimize chemical losses in the laboratory.

The objective of this study was: (1) to monitor the drying kinetics of whole apricots pre-treated by solutions: sucrose, NaCl, and sodium bisulphite in microwave oven at different powers (200, 400, and 800 W), (2) to predict the *DT* and *MR* of drying kinetics of apricot by ANN and ANFIS, (3) to simulate experimental data by 20 mathematical models, (4) to propose a new mathematical model for drying kinetics of treated whole apricot, (5) to compare the results of time prediction by ANN and ANFIS model, and (6) to compare the results of *MR* prediction by the three best models simulated in literature, the model which was created by us, the ANN model, and ANFIS.

2 Experimental

2.1 Sample preparation

The apricot variety used for the experimental study was Mnaa from the Bouzina region, Wilaya of Batna, Algeria. Sampling was done on two to three homogeneous plots. Fruits were randomly selected from several clusters at different heights and orientations, harvested at full maturity (July), and stored in a cold room at 4 °C. Upon arrival at the laboratory, the fruit was sorted according to maturity in order to ensure uniform quality characteristics. The average initial sample weight was 16.420 ± 1.649 g, average width was 33.964 ± 1.915 mm, average length was 33.497 ± 2.138 mm, and moisture ratio of the apricots was determined by vacuum drying at 105 ± 1 °C to a constant weight. The average moisture content of apricots on a wet basis was about 85.93 %. These samples must undergo several pre-treatments before being dried in a microwave oven.

2.2 Pre-treatment of apricot

Before drying, the fruit must undergo several pre-treatments:

- Apricot washing and removal of the stone without opening the fruit (whole apricot).
- Osmotic dehydration: dipping whole apricots in sucrose syrup at 60 °Bx and in 6 % NaCl solution for 18 h at room temperature, then rinsing with hot and cold water to remove the sucrose and salt and inhibit biochemical reactions.
- Sodium bisulphite ($NaHSO_3$) is a microbial stabilizer that protects against mould and insects, anti-browning enzyme: protection against oxidants is used to stabilize colour and taste; whole apricots are immersed for 30 min in 6 % pure anhydrous sodium bisulphite solution, and then rinsed with water to remove excess sodium bisulphite.
- Drainage of whole fruits.
- Drying and monitoring the drying kinetics of whole apricots treated in microwave oven at different powers (200, 400, and 800 W), was conducted according to the following method: In 10 watch glasses, previously cleaned, dried and cooled in a desiccator, we put 16.420 ± 1.649 g of pitted whole apricots (14.110 g wet weight and 2.31 g dry weight). These were then placed in the microwave oven. For the study of microwave drying kinetics, three different powers, 200, 400, and 800 W, were used. After 30 s, each sample was weighed with a precision balance. This operation was repeated regularly at 30-second intervals. Drying was stopped when the residual moisture content of the produce was about 5 %. This operation was repeated for all powers and each type of apricot processing. The curves representing the drying kinetics obtained experimentally were obtained by following the evolution of the *MR* during the drying process by successive weighing until a residual moisture of 5 % was obtained. Using the moisture content of the wet base at any given time, the initial moisture content of the sample's wet base and equilibrium moisture content, the wet base moisture ratio can be calculated using the following formula Eq. (1):[4]

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

where:

M = moist base moisture content at any time t.

M_0 = initial moisture content of the wet base of the sample.

M_e = equilibrium moisture content.

The values of M_e are relatively low compared to those of M or M_0. The error involved in the simplification is negligible,[4] thus moisture ratio (*MR*) was calculated as:

$$MR = \frac{M}{M_0} \tag{2}$$

During the drying process, we monitored the evolution of the mass loss of the whole apricot, to describe the drying kinetics by plotting the curves of the variation of moisture ratio as a function of time $MR = f(t)$.

2.3 Time prediction methods by ANN and ANFIS

Two methods (ANN, ANFIS) were used for time prediction. The database was normalised once in the interval [−1, +1], and divided into two sections: 70 % of the dataset for training, and 30 % of the final samples that were not currently involved in the model training, were used for verification to perform model prediction.[17] The determination coefficient (R^2) and root mean square error (RMSE) were used to assess the performance of the models.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(MR_{\text{exp}} - MR_{\text{pred}})^2}{\sum_{i=1}^{N}(MR_{\text{exp}} - \overline{MR}_{\text{exp}})^2} \tag{3}$$

$$\text{RMSE} = \sqrt{\left(\frac{1}{N}\right)\left(\sum_{i=1}^{N}\left[\left(y_{\text{exp}} - y_{\text{pred}}\right)\right]^2\right)} \tag{4}$$

where MR_{exp} and MR_{pred} are the experimental and predicted dimensionless MR, respectively, and N is the number of observations.[17,18]

2.3.1 ANN modelling

Artificial neural networks (ANNs) are non-linear empirical models. In general, they are composed of many units (neurons) operating in parallel. The functioning of this network is largely determined by the connections between these elements.[19] The neurons are distributed on three layers: input layer, output layer, and hidden layer. The number of neurons in the input layer is related to the number of input variables, and the number of neurons in the output layer is the same as the number of output variables. Between these two layers, there is at least one hidden layer whose number of neurons depends on the application of the network (Fig. 1).[17,20] Optimised neuronal regression through the network architecture is based on the distribution of the database into three sets: (learning, testing, and validation), the transfer functions, the number of neurons in the hidden layer, and the training algorithm.[21]

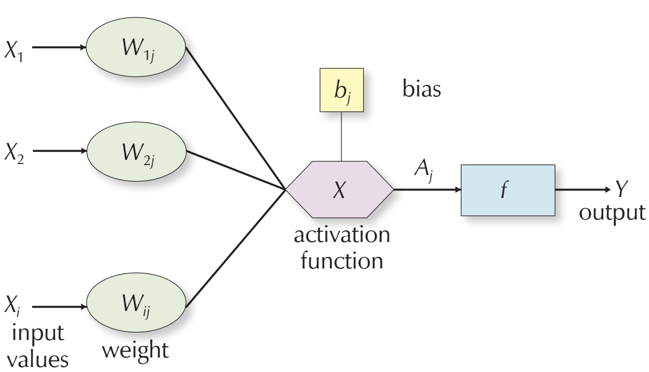

Fig. 1 – Presentation of multilayer neural network

The neuron's output is calculated using relation (Eq. 5):

$$S_J = f\left(\sum_{i=1}^{N} w_{ij}X_i + b_j\right) \tag{5}$$

where w_{ij} is synaptic weight, b_i is bias input, and X_i is the i^{th} input. f is the activation function which can usually be sigmoid or hyperbolic tangent.[22]

The activation functions tansig and logsig can be described as follows:

$$f(a) = \text{tansig}(a) = \frac{2}{1 + e^{-2a}} - 1 \tag{6}$$

$$f(a) = \text{logsig}(a) = \frac{1}{1 + e^{-a}} \tag{7}$$

In this study, ANN was used as a fast and reliable technique to model the drying process. In the ANN, all available data were divided into two parts: one for training and one for model validation. ANN was used to model the moisture ratio of whole apricots, dried in a microwave oven and treated with saccharose, NaCl, and sodium bisulphite. It consisted of several interconnected artificial neurons where each of them gave a single output (Y) induced from all inputs (X_i).[23] The activation functions were in the hidden layer (logsig and tansig). The best final model was selected on the basis of the minimum root mean square error (RMSE) and the maximum coefficient of determination (R^2). Simulation studies were performed using the MATLAB R2013a software.

2.3.2 ANFIS modelling

ANFIS is a technical calculation software that integrates the concept of fuzzy logic in neural networks. The ANFIS model is a kind of neural network that first recognizes drying patterns, and then uses fuzzy inference systems to implement decision-making and differentiation. An adaptive structure of neuro-fuzzy inference system (ANFIS) consists of 5 layers. (1) The fuzzification layer, (2) the rule layer, (3) the normalization layer, (4) the defuzzification layer, and (5) the output layer (Fig. 2).[6] In its theory, ANFIS has a structure including a return propagation algorithm linked to a multilayer fuzzy cum Sugeno neural network with hidden three-layer input and output layers.

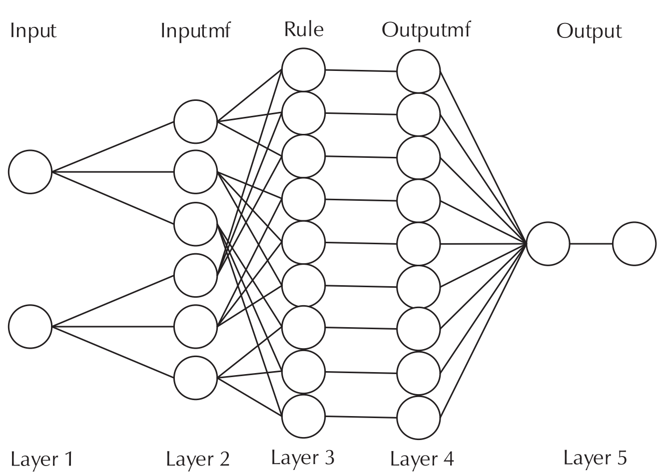

Fig. 2 – Structure of ANFIS

Table 1 – Mathematical models applied to the drying curves

Model name	Model	Reference
Lewis	$MR = \exp(-kt)$	24
Page	$MR = \exp(-kt^n)$	25
Modified Page	$MR = \exp(-(kt)^n)$	26
Wang and Singh	$MR = 1 + a_1t + a_2t^2$	27
Henderson & Pabis	$MR = a\exp(-kt)$	28
Logarithmic	$MR = a\exp(-kt) + c$	29
Two Term	$MR = a\exp(-kt) + b\exp(-k't)$	14
Midilli	$MR = a\exp(-kt^n) + bt$	30
Verma et al.	$MR = a\exp(-kt) + (1-a)\exp(-k't)$	31
Modified Henderson & Papis	$MR = a\exp(-kt) + b\exp(-k't) + c\exp(-k''t)$	31
Two_term exponential	$MR = a\exp(-kt) + (1-a)\exp(-kat)$	32
Diffusion approach	$MR = a\exp(-kt) + (1-a)\exp(-kat)$	26
Simplified Fick's diffusion	$MR = a\exp(-k(t/L^2))$	33
Modified Page III	$MR = a\exp(-k(t/L^2)^n)$	33
Demir et al.	$MR = a\exp(-kt^n)+bt$	27
Weibull	$MR = a\exp(-(t/a)^n)$	34
Hii	$MR = a\exp(-kt^n) + b\exp(-k_1t^n)$	34
Keskes et al.	$MR = a\exp(-kt) + b\exp(-kt^{1/n}) + c$	34
Geometric	$MR = at^{-1}$	35
Logistic	$MR = \dfrac{a}{(1+a\exp(kt))}$	35
Proposed model	$MR = \dfrac{(a+bx)}{(1+ct+dt^2)}$	**This study**

a, a_1, a_2, b, c, d, coefficients and n, specific exponent of each drying equation; k, k', k'', k_1 specific coefficients of each drying equation, t is the drying time.

In this study, the ANFIS tool was used to predict the time of drying kinetics of whole apricots treated with sucrose solution, NaCl, and sodium bisulphite in microwave oven at different powers (200, 400, and 800 W). There were five input parameters, including microwave power, total weight of whole apricots, water content, dry matter content, and *MR*, and the output was the *DT*.

2.4 Mathematical modelling of drying whole apricots

In this section, we proposed a new semi-empirical model. This model was compared to twenty models in the literature that were studied by the researchers. In order to describe the moisture ratio of whole apricots treated with sucrose, NaCl, and sodium bisulphite, and to determine the most appropriate empirical equation, the parameters of the mathematical model were optimised using a sigma plotting program version 10. Our model and the other 20 models are presented in Table 1.

The correlation coefficient (R^2) is the first criterion used to select the best model that defines the experimental drying data[17] In addition, a reduction in the chi-square (χ^2) and the mean square error of the square root (RMSE) were used to determine the quality of the fit.[31] These parameters are calculated by the Eqs. (3) and (4) and the following Eq. (8):

$$\chi^2 = \left[\frac{\sum_{i=1}^{N}(MR_{\exp} - MR_{\text{pre}})^2}{N-n}\right] \tag{8}$$

where $MR_{\exp}$ and MR_{pred} are the experimental and predicted dimensionless *MR*, respectively, N is the number of observations, and n is the number of model constants.[18]

2.5 Moisture ratio (*MR*) prediction methods by ANN and ANFIS

In this section, models (ANN, ANFIS) were also used for predicting *MR*. The coefficient of determination (R^2) and adjusted coefficient were used for the performance of the models Eqs. (4)–(6).

3 Results and discussion

3.1 Drying kinetics

During the drying process, the evolution of the apricot moisture ratio (*MR*) was monitored as a function of time (*t*) with: $MR = f(t)$ with a type of microwave drying; knowing that every 30 s of microwave drying corresponds to one cycle.

3.1.1 Influence of power on kinetics of microwave drying

The changes in moisture ratio (*MR*) as a function of drying time (*t*) for the three microwave powers (200, 400, and 800 W) are shown in Fig. 3.

The moisture content of fresh apricots was approximately 85.93 %. Whole apricots were dried to a moisture content of 5 %. The drying curves for the pre-treated microwave-dried apricots are shown in Fig. 3. In general, the drying kinetics of microwave-treated apricots were similar to those found by *Toğrul and Pehlivan*.[36] One can notice regularly decreasing curves. This decrease corresponds to the elimination of free water. Initially, the water content was high in the apricot and less microwave energy was absorbed; the apricot was heated by the radiation, and therefore, the evaporation of water was accelerated.[37] However, as drying progresses, water must move from the interior of the plant tissue to the surface, which depends on liquid diffusion, capillary movement, and surface diffusion, and slows the rate of the water evaporation.[38]

Drying kinetics at 800 and 400 W were the shortest times (270 and 420 s, respectively), whereas, drying kinetics at 200 W were the longest (570 s). Therefore, our frame shows a remarkable influence of power on microwave drying kinetics (Fig. 3). These results are similar to those found by *Horuz et al.*,[39] who studied the microwave drying kinetics of apricots at three powers 120, 150, and 180 W. These authors revealed that the drying time increased from 157 to 409 min.

Apricots dried in microwave oven at 400 and 800 W power, treated with sucrose solution and NaCl had the shortest duration compared to the sodium bisulphite treatment, because a considerable amount of water from the tissue immersed in concentrated aqueous solutions had already been removed by osmotic dehydration (osmosis phenomenon). The osmotic pressure difference caused a mass transfer between the fruit tissue and the osmotic agent.

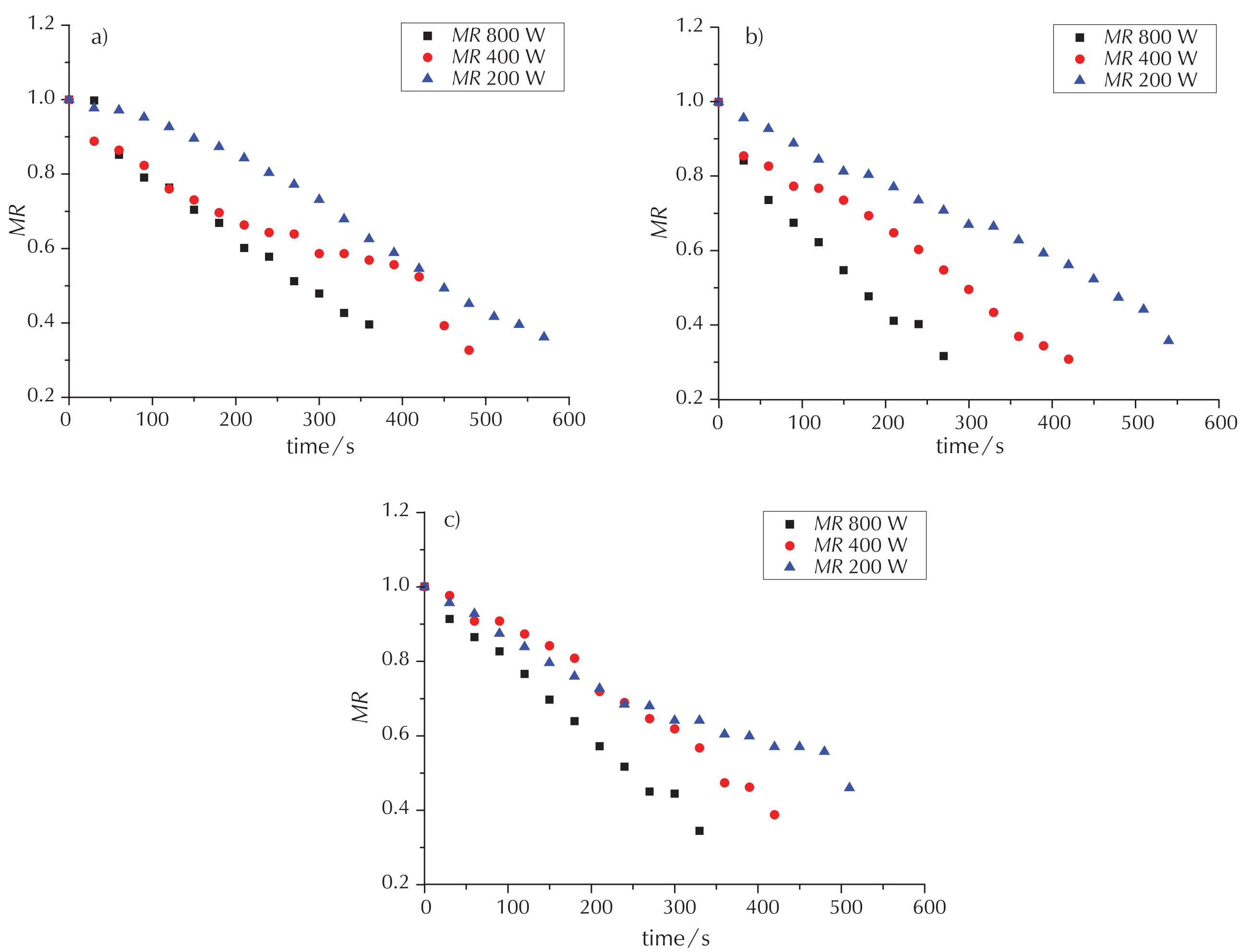

Fig. 3 – Evolution of *MR* over time for apricots treated in a solution of: (a) sucrose, (b) NaCl, and (c) sodium bisulphite in a microwave oven

Two opposite flows appeared: diffusion of water from fruit cellular tissue (water loss, *WL*), and diffusion of osmotic agent into cells (solid gain, *SG*). The intensity of mass transfer depends on the type of osmotic agent, temperature, and concentration of the osmotic solution, the power of the microwave, speed of agitation, ratio between the fruit and the osmotic agent, and the mass ratio between the fruit and the osmotic agent, which justifies the long drying time of whole apricots treated with sodium bisulphite compared to apricots treated with sucrose and NaCl.[40]

At 200 W power, the shortest drying time was recorded for NaCl-treated apricots (510 s), followed by the other treatments. The longest time was recorded for drying apricots treated with sodium bisulphite (510 to 570 s). This difference was due to the treatment agent used. The use of pre-treatment improved the moisture migration of whole apricots and reduced the drying time. This is confirmed by blanching and dipping in a saline solution that promotes moisture migration from the inner regions of the food crop.[41] The increase in microwave power decreased drying time. The probability analysis of each factor indicated that treatments investigated, and sodium and microwave power had a significant effect on apricot water loss.

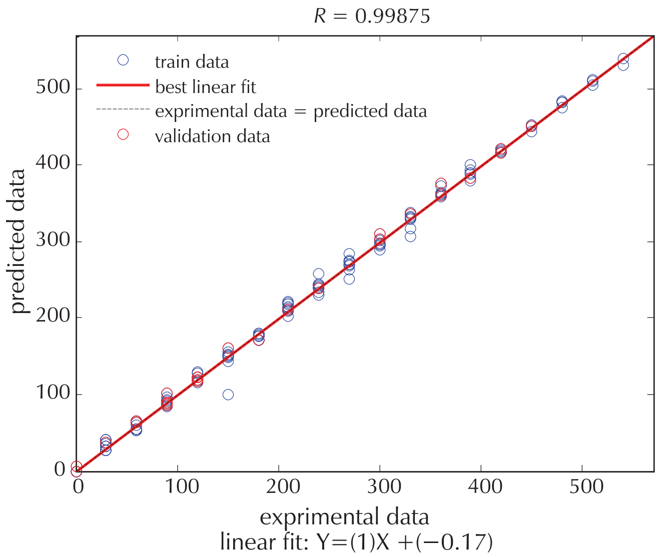

Fig. 4 – Predicted values relative to experimental time tansig values of the ANN validation phase and training phase model

3.2 Time prediction methods by ANN and ANFIS

3.2.1 ANN modelling

In this study, ANN was used to predict the drying time. In order to obtain a better result, the feedback propagation network with Levenberg–Marquard (LM) learning algorithm was chosen, after which this network was optimised with three activation functions (tansig, logsig, and purelin), and with many neurons of the hidden layer (3 : 15). Five input parameters, including microwave power (W), total apricot weight (g), moisture content (%), dry matter content (%), and moisture ratio (*MR*), while the output parameter was the drying time (s).

The results of modelling ANN for *MR* time prediction are presented in Table 2.

Table 2 reveals that the results are almost equal from the point of view of correlation coefficient and RMSE in the three phases (training, validation, and all data). Therefore, the 1st architecture was chosen since a small increase in the correlation coefficient and a small decrease in RMSE was found compared to the 2nd architecture. The results of Table 2 are graphically presented in Figs. 4 and 5. Fig. 6 again shows the efficiency of our model which was chosen in this part.

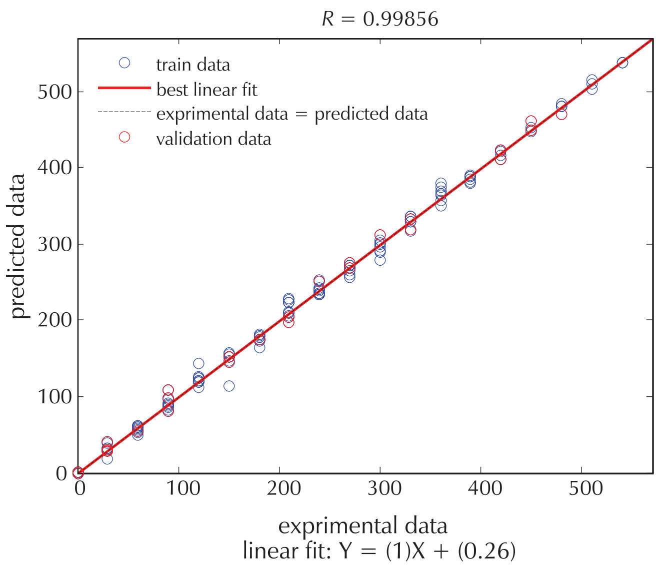

Fig. 5 – Predicted values relative to experimental time logsig values of the ANN validation phase and training phase model

Table 2 – Performances of the different ANN architectures of time

		Activation function		Coefficients of determination			RMSE $\cdot 10^{-6}$		
Learning algorithm	Network architecture	Hidden layer	Output layer	Training	Validation	All	Training	Validation	All
Levenberg–Marquard	[5-15-1]	tansig	purelin	0.99864	0.99919	0.99875	7.8056	6.0607	7.4892
	[5-15-1]	logsig	purelin	0.99844	0.99891	0.99856	8.0176	7.8217	7.9788

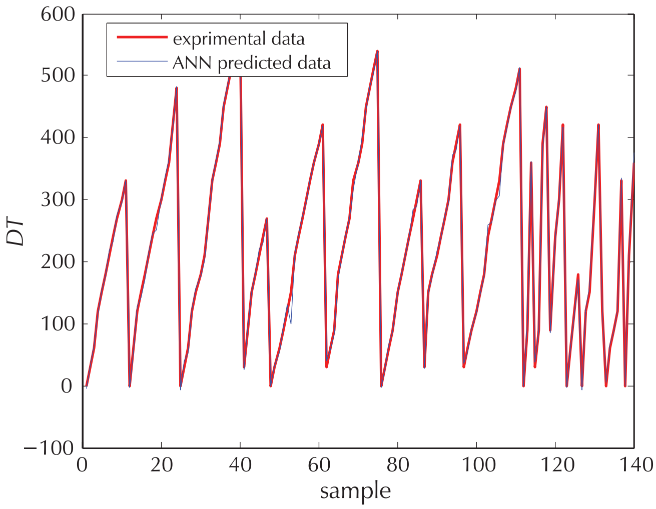

Fig. 6 – Relationship between experimental data and predicted data of samples

3.2.2 ANFIS modelling

In this work, the drying time (*DT*) prediction technique of microwave-treated whole apricots by ANFIS was used. There were five input parameters, including microwave power, total apricot weight, moisture content, dry matter content, and moisture ratio (*MR*). Table 3 reveals the best algorithms for ANFIS. The correlation coefficient (R^2) is very high; on the other hand, the statistical indicator is very low (RMSE), which indicates a good fit or performance, and suggests that ANFIS can be used effectively to predict the drying time. The result is better ($R^2 = 0.9921$) than that obtained by *Satorabi et al.*, who found a correlation coefficient of $R^2 = 0.973$. Knowing that the only difference was in the volume of the dried apricot fruit, we used the whole fruit. On the other hand, *Satorabi et al.* used apricot slices.[5]

Table 3 shows that the results are almost equal in terms of the correlation coefficient and the RMSE in all three phases (training, validation, and all data). Therefore, the training phase was chosen as a slight increase in the correlation coefficient (0.99414), and a small decrease in RMSE (16.2664) was found compared to the phases of all data and validation (R^2: 0.99211, RMSE: 18.7286), and (R^2: 0.98304, RMSE: 26.6716), respectively. The results in Table 3 are graphically shown in Fig. 7. Fig. 8 shows the *DT* values as a function of the ANFIS estimate for unseen data points (test data). It can be seen that the system was well trained to model these parameters. The calculated *R* value for the *DT* estimate was 0.9921, showing a high correlation between the predicted and experimental values. In general, this model simply explains the highly nonlinear process, including microwave drying, without the need to establish the complicated mechanisms involved.

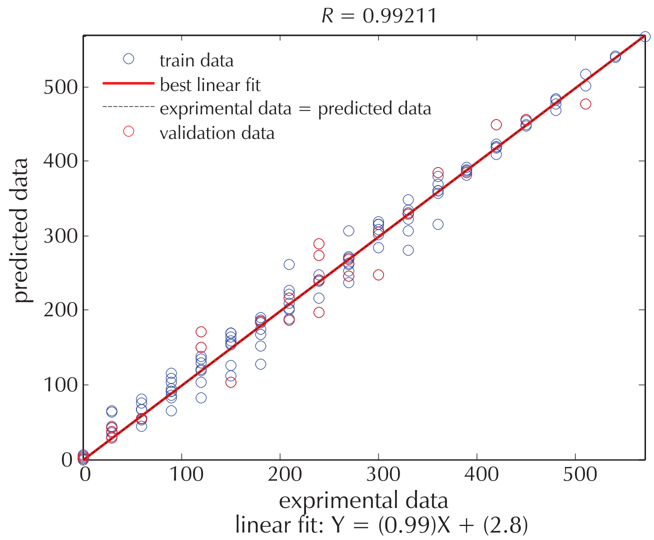

Fig. 7 – Predicted values relative to experimental time values of the ANFIS validation phase and training phase model samples

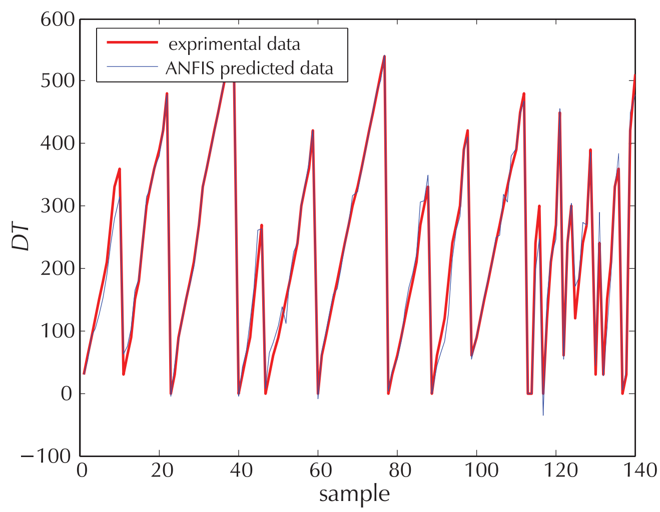

Fig. 8 – Relationship between experimental data and predicted data of samples

Table 3 – Performance of the different ANFIS architectures of time

ANFIS	Membership function type		Train FIS	Coefficients of correlation			**RMSE · 10^{-6}**		
Number of membership functions	Input	Output	Optimisation method	Training	Validation	All	Training	Validation	All
[2 2 2 2 2]	gbellmf	linear	hybrid	0.99414	0.98304	0.99211	16.2664	26.6716	18.7286

3.2.3 Comparison between the drying times of ANN and ANFIS

Comparison between the ANN model and the ANFIS model was based on the statistical parameters (R^2 and RMSE). Table 4 shows the comparison between the drying times (*DT*) of ANN and ANFIS. According to Table 4, the ANN model contains a higher correlation coefficient (0.99919) and a low RMSE value (6.0607) by contribution ANFIS (R^2 = 0.99414, RMSE = 16.2664). The ANN model is the most appropriate for the prediction of drying time of whole apricot.

Table 4 – Comparison between the drying times (*DT*) of ANN and ANFIS

Model	**RMSE · 10⁻⁶**	R^2
ANN(*DT*)	**6.0607**	**0.99919**
ANFIS(*DT*)	16.2664	0.99414

3.3 Modelling of the drying kinetics of apricots

In this work, the drying kinetics were modelled by three mathematical models (*Modified Henderson–Pabis*, *Henderson-Pabis*, and *Two Term*), and proposed model. Fig. 9 illustrates the obtained results. The calculated values of the used statistical parameters are shown in Tables 5–7 with the most suitable model marked in bold.

The three models and the proposed model were compared in terms of the values of the coefficient of determination (R^2), the reduced chi-square (χ^2), and the square root mean square error (RMSE). Under the studied experimental conditions, the values of R^2, χ^2, and RMSE range from 0.9407 to 0.9989, $3.05 \cdot 10^{-7}$ to $1.82 \cdot 10^{-3}$, and $2.23 \cdot 10^{-7}$ to $1.21 \cdot 10^{-3}$, respectively. The high values of R^2 and the low values of χ^2 and RMSE for the three simulated models, and the model proposed in this study indicate a good consistency between these models and the experimental results. The proposed model was chosen to adequately describe the drying behaviour of whole apricots treated with NaCl, sucrose, and sodium bisulphite at microwave powers of 200 and 400 W, respectively, due to a high value of R^2 and low values of χ^2 and RMSE (see Tables 5–7).

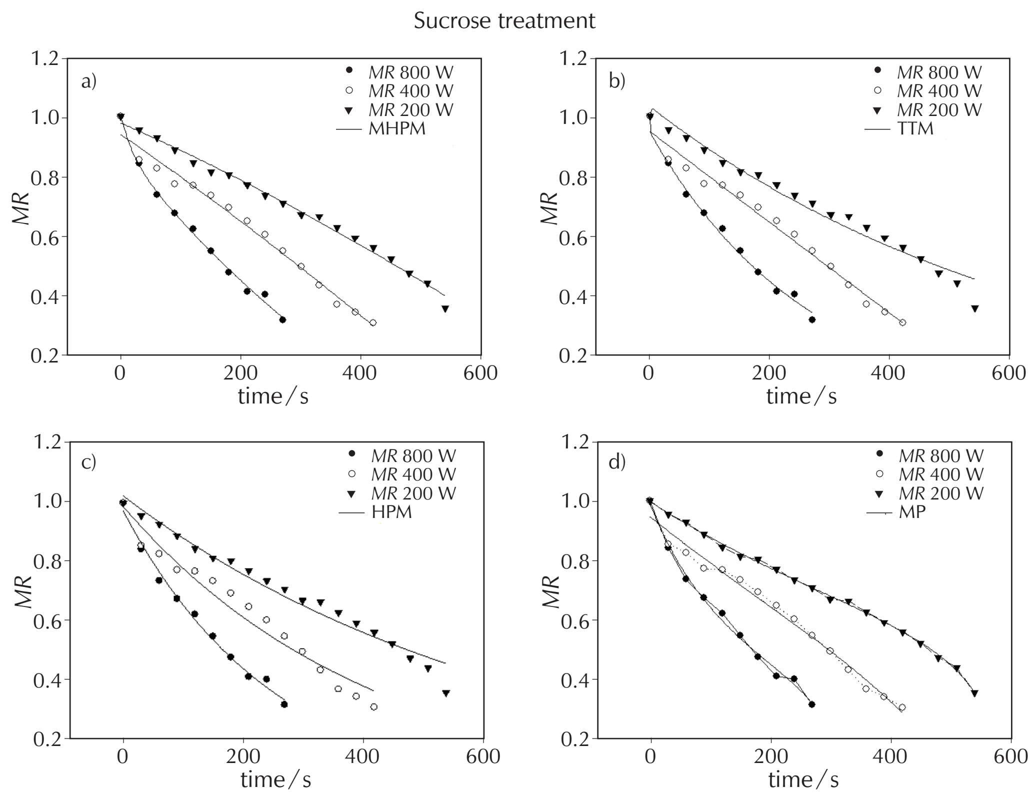

Fig. 9 – Modelling of drying kinetics of whole apricots by microwave oven: (a) *Modified Henderson & Pabis* model, (b) *Henderson–Pabis* model, (c) *Two Term* model, and (d) proposed model

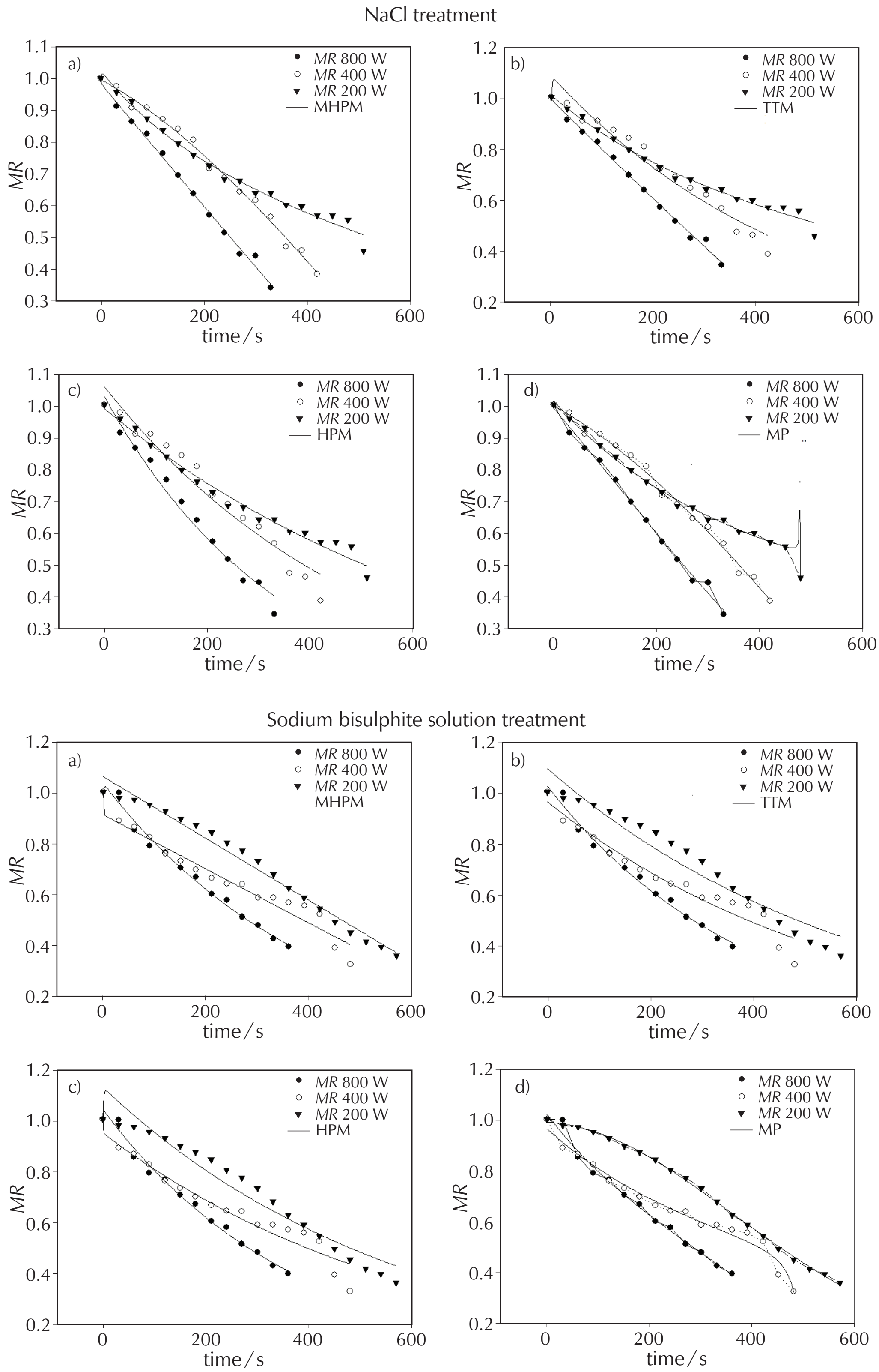

Fig. 9 – (continued)

Table 5 – Modelling of drying kinetics of sucrose-pre-treated apricots in a microwave oven

MN	Power	Parameter							Parameter statistics		
		A	*k*	*B*	*k′*	C	*k′′*	D	R^2	χ^2	RMSE
1	200	64.425	$9.13 \cdot 10^{-5}$	19.467	0.00025	−43.979	$2.50 \cdot 10^{-15}$		0.992	$1.26 \cdot 10^{-4}$	$8.59 \cdot 10^{-5}$
	400	24.533	0.000183	−6.174	0.00050	−17.419	$2.90 \cdot 10^{-13}$		0.983	$1.23 \cdot 10^{-5}$	$7.38 \cdot 10^{-6}$
	800	0.114	0.0477	−0.801	$6.03 \cdot 10^{-10}$	1.686	0.0015		0.996	**$1.03359 \cdot 10^{-5}$**	**$4.134 \cdot 10^{-6}$**
2	200	1.0232	0.0015						0.969	0.0005514	0.00049
	400	0.9874	0.0024						0.9595	0.00020229	0.00017
	800	0.9724	0.004						**0.9911**	**$2.04 \cdot 10^{-5}$**	**$1.63 \cdot 10^{-5}$**
3	200	0.145	0.8998	1.0317	0.0015				0.9702	0.00067468	0.00053
	400	−0.083	$2.31 \cdot 10^{-5}$	−65.508	$8.71 \cdot 10^{-16}$				**0.9833**	**$3.05 \cdot 10^{-7}$**	**$2.23 \cdot 10^{-7}$**
	800	−7.296	2.2859	0.945	0.0038				**0.9947**	**$7.54 \cdot 10^{-5}$**	**$4.52 \cdot 10^{-5}$**
4	200	0.997		−0.0017		−0.0003		$-1.826 \cdot 10^{-6}$	**0.9985**	**$4.79388 \cdot 10^{-5}$**	**$3.84 \cdot 10^{-5}$**
	400	0.946		−0.0018		−0.0001		$-1.74 \cdot 10^{-6}$	**0.9846**	**$3.448 \cdot 10^{-6}$**	**$1.72 \cdot 10^{-5}$**
	800	0.990		−0.003		−0.002		$-1.24 \cdot 10^{-6}$	0.9946	$4.6 \cdot 10^{-4}$	$4.48 \cdot 10^{-3}$

MN: Model name; 1: Modified Henderson–Pabis model; 2: Henderson–Pabis model; 3: Two Term model; 4: Proposed model

Table 6 – Modelling of drying kinetics of NaCl-pre-treated apricots in a microwave oven

MN	Power	Parameter							Parameter statistics		
		A	*k*	*B*	*k′*	C	*k′′*	D	R^2	χ^2	RMSE
1	200	−0.0238	0.6307	0.8982	0.0011	0.1256	0.0085		0.9873	0.00025785	0.0001719
	400	8.436	0.0006	−2.5024	0.0017	−4.9394	$1.96 \cdot 10^{-13}$		**0.993**	**$4.01 \cdot 10^{-6}$**	**$2.41 \cdot 10^{-6}$**
	800	−7.263	$7.12 \cdot 10^{-17}$	18.2469	0.0001	0.0162	11.5651		**0.9952**	**0.00037777**	**0.0001888**
2	200	0.9872	0.0014						0.9831	$3.86 \cdot 10^{-5}$	$3.43 \cdot 10^{-5}$
	400	1.0561	0.0019						0.9527	0.00060574	0.000524
	800	1.0251	0.0028						0.9808	0.0003971	0.0003309
3	200	0.145	0.0058	0.8628	0.0011				0.9868	0.00012188	$9.479 \cdot 10^{-5}$
	400	−0.0836	0.7102	1.0836	0.002				0.9614	0.00059726	0.0004379
	800	−7.2965	$1.26 \cdot 10^{-6}$	8.2874	0.0002				**0.9949**	**0.00182246**	**0.0012149**
4	200	1.0124		−0.002		−0.0001		$-3.70 \cdot 10^{-6}$	**0.996**	**$8.97 \cdot 10^{-4}$**	**$6.98 \cdot 10^{-4}$**
	400	0.9964		−0.0016		−0.0007		$7.35 \cdot 10^{-7}$	**0.993**	**$1.99299 \cdot 10^{-7}$**	**$1.46 \cdot 10^{-7}$**
	800	0.9887		−0.0018		0.0001		$9.02 \cdot 10^{-7}$	**0.9949**	**$3.1865 \cdot 10^{-6}$**	**$2.12 \cdot 10^{-6}$**

MN: Model name; 1: Modified Henderson–Pabis model; 2: Henderson–Pabis model; 3: Two Term model; 4: Proposed model

Table 7 – Modelling of drying kinetics of sodium bisulphite-pre-treated apricots in a microwave oven

MN	Power	Parameter							Parameter statistics		
		A	*k*	*B*	*k′*	C	*k′′*	D	R^2	χ^2	RMSE
1	200	−0.0238	$2.33 \cdot 10^{-5}$	0.0889	29.6903	−44.7549	$1.64 \cdot 10^{-15}$		0.9596	$1.32 \cdot 10^{-4}$	$9.26 \cdot 10^{-5}$
	400	8.4369	$3.05 \cdot 10^{-16}$	−78.503	$1.01 \cdot 10^{-16}$	158.0939	$7.67 \cdot 10^{-6}$		**0.9829**	**$2.11 \cdot 10^{-3}$**	**$1.37 \cdot 10^{-3}$**
	800	−7.2631	0.8498	1.0924	0.0024	−0.0588	$1.72 \cdot 10^{-11}$		**0.990**	**$4.87 \cdot 10^{-6}$**	**$2.62 \cdot 10^{-6}$**
2	200	1.0925	0.0016						0.9407	0.00037274	0.0003313
	400	0.9623	0.0017						0.9442	0.00064805	0.0005718
	800	1.0237	0.0025						**0.988**	**$5.2162 \cdot 10^{-5}$**	**$4.1729 \cdot 10^{-5}$**
3	200	−0.1255	0.7402	1.1255	0.0017				**0.9899**	0.00026758	0.0002140
	400	0.0535	84.5644	0.9465	0.0016				0.9484	0.00026758	0.0007403
	800	−0.0389	15.0223	1.0389	0.0026				**0.9899**	**$1.513 \cdot 10^{-5}$**	**$1.048 \cdot 10^{-5}$**
4	200	0.9905		−0.0009		−0.0007		$2.55 \cdot 10^{-6}$	**0.9895**	**$4.79388 \cdot 10^{-5}$**	**$3.84 \cdot 10^{-5}$**
	400	0.9635		−0.002		$-8.92 \cdot 10^{-5}$		$7.9 \cdot 10^{-7}$	**0.9811**	**0.006270471**	**$4.80 \cdot 10^{-3}$**
	800	1.0201		−0.0019		0.0008		$-3.03 \cdot 10^{-6}$	**0.9895**	**$4.70535 \cdot 10^{-5}$**	**$3.26 \cdot 10^{-5}$**

MN: Model name; 1: Modified Henderson–Pabis model; 2: Henderson–Pabis model; 3: Two Term model; 4: Proposed model

3.4 Predictive time testing

After testing the *MR* values for experimental time and predicted time of the proposed model with three treatments, it was concluded that the same values for MR_{exp}, MR_{pre}, and MR_{preT} were obtained, confirming the effectiveness of the time model (see Fig. 10).

3.5 *MR* prediction methods by ANN and ANFIS

3.5.1 Artificial neural network modelling

In this study, ANN was used to predict *MR*. In order to obtain better results, the feedback propagation network with learning algorithms (LM) was chosen, after which this net-

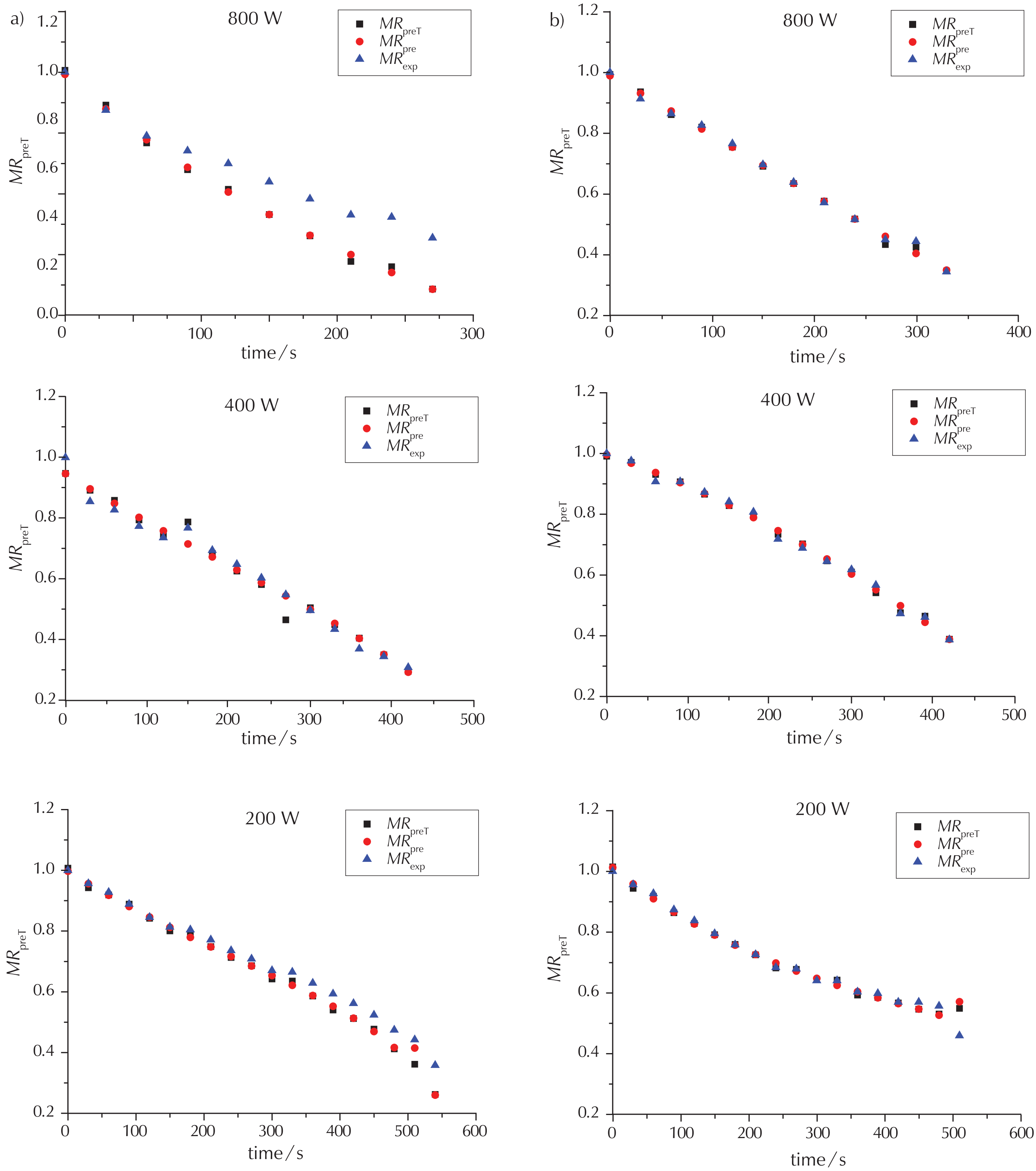

Fig. 10 – Evolution of the moisture ratio (*MR*) exp, pre, and preT by the proposed model as a function of time at powers (200, 400, and 800 °C) and treatments. Cases: a: sucrose and b: NaCl.

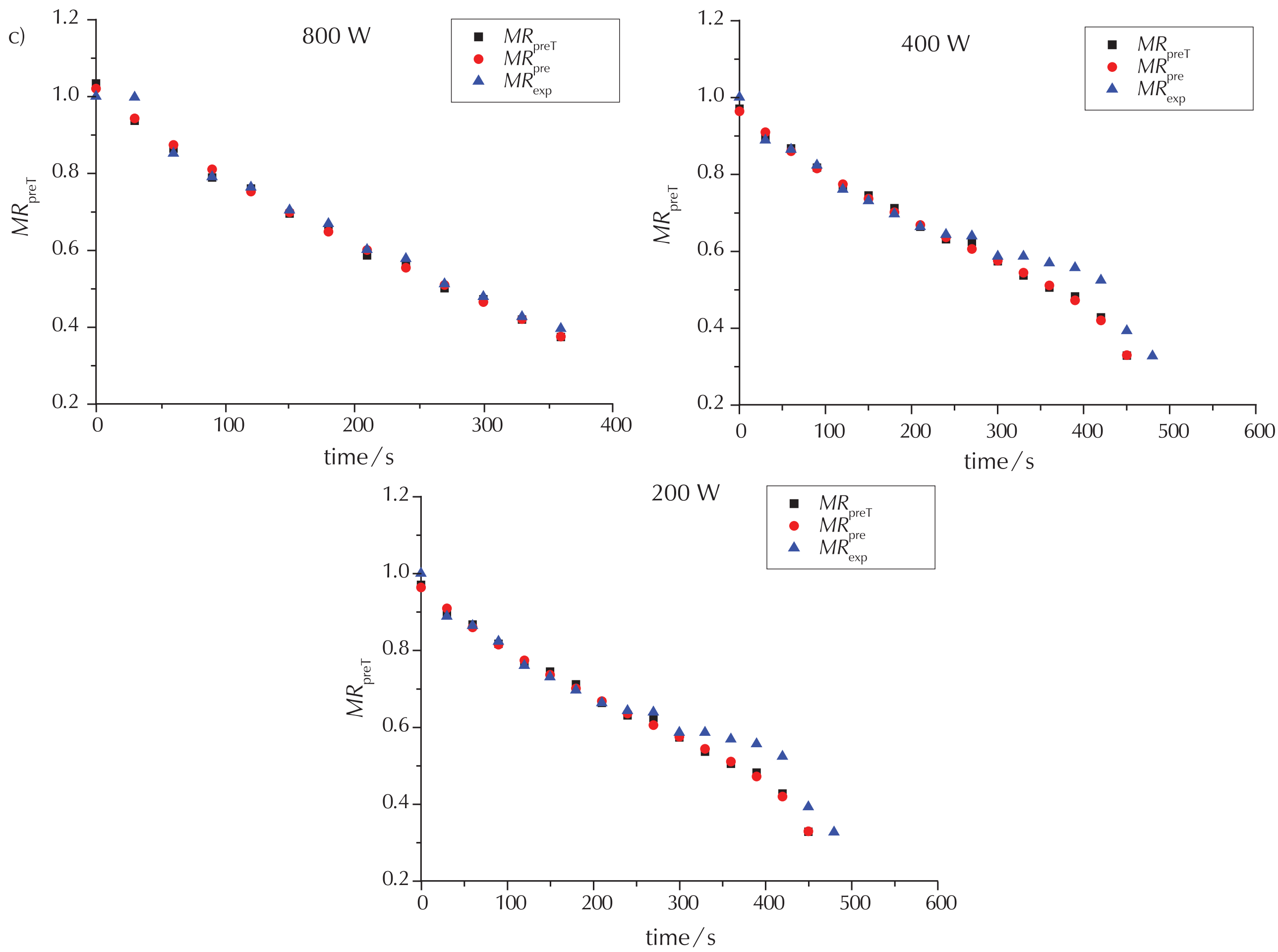

Fig. 10 – (continued) Case: c: sodium bisulphite

work was optimised with three activation functions (tansig, logsig, and purelin) (see Figs. 11 and 12), and with many neurons of the hidden layer (3 : 15). Five input parameters, including microwave power, total apricot weight, moisture content, dry matter content, and drying time, and one output parameter is the moisture ratio. This model was allowed to mix the three treatments (sucrose solution, NaCl, and sodium bisulphite), create a unique model suitable for each treatment, and test each treatment alone. The results of ANN modelling for the time prediction to the mixture of three *MR* treatments are presented in Table 8.

Table 8 and Fig. 13, reveal that there is not much difference between the obtained results, since the results are almost equal. The architecture [5-12-1] was chosen according to the logsig activation function in the hidden layer and the purelin function in the output layer.

The architecture [5-12-1] was chosen as their parameter numbers were 85 as the architecture [5-15-1], which was 106.

Table 8 – Performances of the different ANN architectures of *MR*

		Activation function		Correlation coefficient			RMSE		
Learning algorithm	**Network architecture**	Hidden layer	Output layer	**Training**	**Validation**	**All**	**Training**	**Validation**	**All**
Levenberg–Marquard	[5-15-1]	tansig	purelin	0.9996	0.9997	0.99962	0.0058	0.0052	0.0057
	[5-12-1]	logsig	purelin	0.99958	0.99942	0.99956	0.0059	0.0062	0.0059

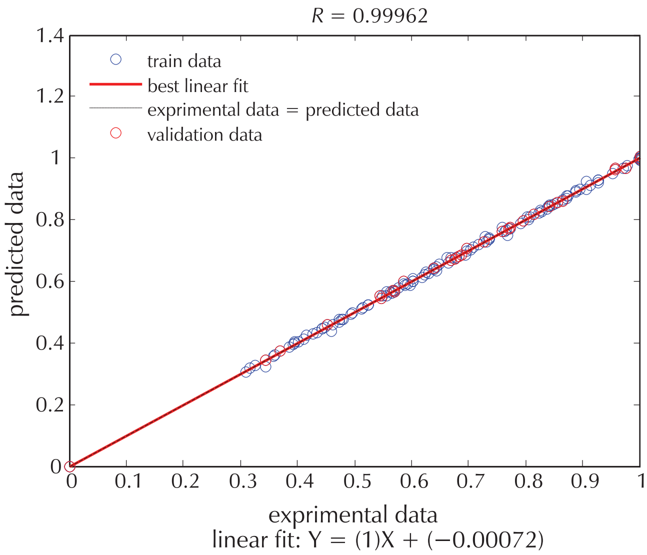

Fig. 11 – Predicted values relative to experimental *MR* tansig values of the ANN validation phase and training phase model

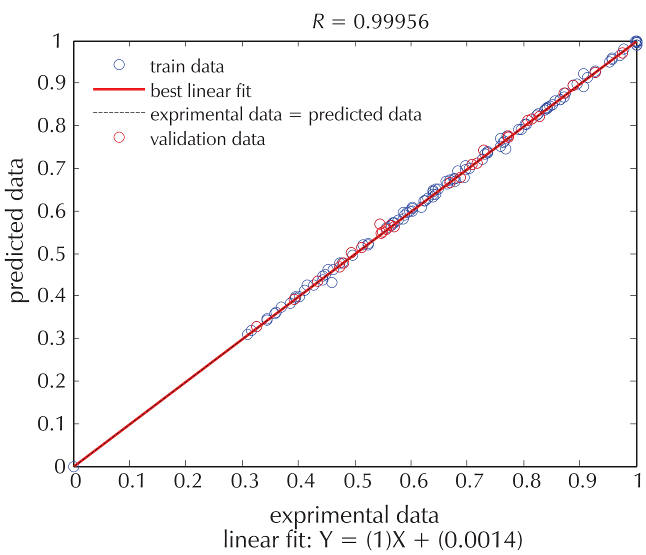

Fig. 12 – Predicted values relative to experimental *MR* logsig values of the ANN validation phase and training phase model

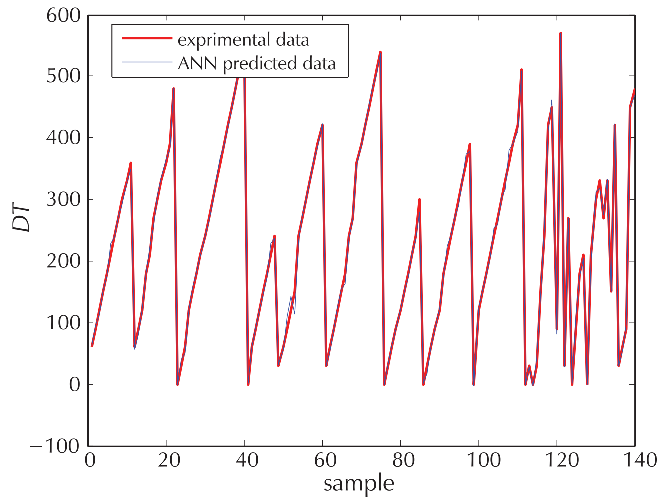

Fig. 13 – Relationship between experimental data and predicted data of samples

Considering the very high estimated R^2 value and the low RMSE value for logsig and tansig *MR*, it was concluded that ANN can be used effectively to predict *MR*.

3.5.3 ANFIS modelling

In this work, the weighting algorithms and functions (gbellmf), were chosen for the input and linear for the output as well as many nodes for each input to get the right result. Five input parameters, including microwave power, total apricot weight, moisture content, dry matter content, and drying time, and one output parameter is the moisture ratio. The ANFIS predictive technique was used to predict *MR*.

Table 9 reveals the best algorithms for the ANFIS array, and the high R^2 and low RMSE values for logsig and tansig RMS indicate good fit or performance, and suggest that ANFIS can be used effectively to predict *MR*. In addition to data quality, the effectiveness of a typical ANFIS prediction also depends on the number of rows and columns of input data. The results of ANFIS modelling for the time prediction to the mixture of three *MR* treatments are presented in Table 9. It was found that the architecture of [2 2 2 2 2] Training ANFIS (*MR*) model gave the lowest RMSE (0.0063) and a high value of R^2 (0.99951) for the All ANFIS (*MR*) and Val ANFIS (*MR*), respectively, but these values were closer to the others. The predicted results were plotted against the experimental values as shown in Figs. 14 and 15.

Table 9 – Performances of the different ANFIS architectures of *MR*

ANFIS	MF Type		Train FIS	Coefficient of correlation			RMSE		
No. of membership functions	Input	Output	Optimisation method	Training	Validation	All	Training	Validation	All
[2 2 2 2 2]	**gbellmf**	**linear**	**hybrid**	**0.99951**	**0.99867**	**0.99937**	**0.0063**	**0.0096**	**0.0071**

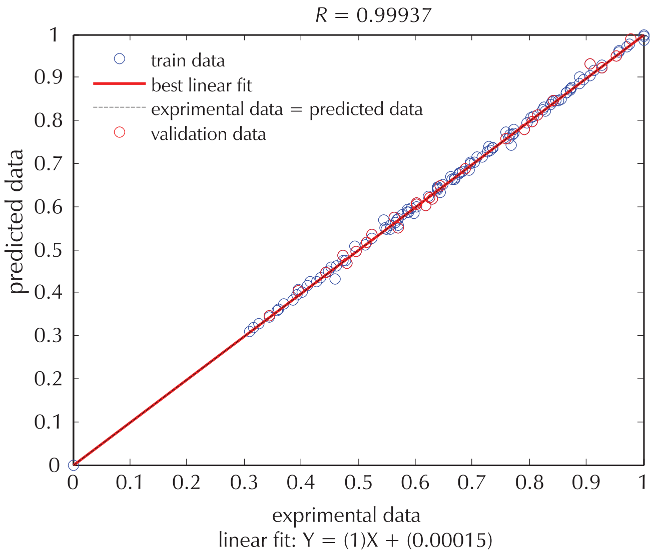

Fig. 14 – Predicted values relative to experimental *MR* values of ANN validation phase and training phase model

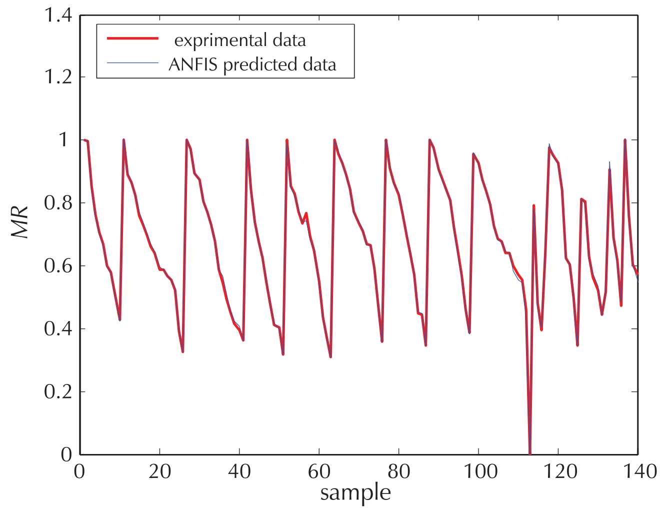

Fig. 15 – Relationship between experimental data and predicted data of samples

3.6 Comparison between the moisture ratio of proposed model, ANN and ANFIS

The comparison between the three models was based on the statistical parameters (R^2 and RMSE) and the number of epochs of each model. Tables 10 and 11 show the three models mixed and associated with the three treatments (sucrose, NaCl and sodium bisulphite) and unmixed, respectively.

According to Table 10, the ANN model contained a higher correlation coefficient (0.9991) and low RMSE (0.0059) value followed by ANFIS (R^2 = 0.9950, RMSE = 0.0071), and

Table 10 – Comparison between the proposed models, ANN, and ANFIS had three mixed treatments (sucrose, NaCl, and sodium bisulphite)

Model	RMSE	MAE	*R*	R^2	R^2_{adj}
PM(*MR*)	0.0878	0.0215	0.9973	0.9947	0.9909
ANN(*MR*)	**0.0059**	**0.0039**	**0.99956**	**0.9991**	**0.9991**
ANFIS(*MR*)	0.0071	0.0046	0.99937	0.99500	0.9987

Table 11 – Comparison between the proposed models, ANN and ANFIS had three unmixed treatments at 200, 400, and 800 W

Pre-treatment and microwave power	Proposed model		ANN		ANFIS	
Sucrose 200 W	RMSE	0.29334845	RMSE	$1.1306 \cdot 10^{-5}$	RMSE	$8.57052 \cdot 10^{-8}$
	R^2	0.99817254	R^2	0.99999993	$\boldsymbol{R^2}$	**0.999999998**
400 W	RMSE	$4.1564 \cdot 10^{-7}$	RMSE	0.00864375	RMSE	0.00051987
	R^2	**0.99999998**	R^2	0.99998547	R^2	0.9999739
800 W	RMSE	0.37801268	RMSE	0.00400916	RMSE	$2.29682 \cdot 10^{-7}$
	R^2	0.95952499	R^2	0.99999456	$\boldsymbol{R^2}$	**0.999999975**
NaCl 200 W	RMSE	$6.3983 \cdot 10^{-5}$	RMSE	0.12055309	RMSE	0.00149693
	R^2	**0.99999957**	R^2	0.99999098	R^2	0.99995703
400 W	RMSE	$1.7896 \cdot 10^{-5}$	RMSE	0.00041066	RMSE	0.00020181
	$\boldsymbol{R^2}$	**0.99999933**	R^2	0.99998454	R^2	0.9999924
800 W	RMSE	0.00048178	RMSE	0.00264449	RMSE	0.00010973
	R^2	0.9999515	$\boldsymbol{R^2}$	**0.99999845**	R^2	0.99999298
Sodium bisulphite 200 W	RMSE	0.00981046	RMSE	0.0041978	RMSE	0.00087767
	R^2	0.99974863	$\boldsymbol{R^2}$	**0.99999783**	R^2	0.99997751
400 W	RMSE	0.10634142	RMSE	0.00116169	RMSE	0.00127885
	R^2	0.99583571	R^2	**0. 99995451**	R^2	0.99994992
800 W	RMSE	0.00273393	RMSE	0.18713204	RMSE	0.00036377
	R^2	0.99984963	R^2	**0.99999751**	R^2	0.99997999

finally the proposed model (R^2 = 0.9947, RMSE = 0.0878), but these values are closer to each other and there is no significant difference between them. According to the number of epochs, the proposed model was the most suitable for the drying of processed whole apricot since it contained 4 epochs, followed by ANN (85) and finally ANFIS (309).

According to Table 11 and the R^2 and RMSE values, the ANFIS model is the most suitable for describing sucrose-treated dried apricots, the proposed model for NaCl-treated apricots, and the ANN model for sodium bisulphite treated apricots. However, according to the number of epochs, the proposed model is the most suitable for drying treated whole apricots since it contains 4 epochs. The proposed model may be mainly used in future studies in the agri-food production industries, as it is inexpensive (4 epochs).

These results were comparable to those found by *Jahanbakhshi et al.*, who used ANN and ANFIS models to predict the drying behaviour of pistachio kernel in microwave dryer using US pre-treatment by *Midilli et al.* model, ANN and ANFIS, and analysing the effect of indirect independent variables in predicting the moisture ratio in pistachio kernel. They reported that the ANFIS model was better than the ANN model in terms of its higher R^2 and lower MSE.[41] *Abbaspour-Gilandeh et al.*, predicted the kinetics, energy, and exergy of quince under the hot air dryer using ANN and ANFIS. The ANFIS model showed better ability to predict these parameters than artificial neural networks.[6]

4 Conclusion

The results obtained showed that the drying time decreased with the increasing microwave power. Impregnation of apricots in a salty solution (6 %) as an innovative and inexpensive pre-treatment method gave the shortest drying time compared to the other treatments. Simulation of experimental data indicated that, out of the twenty semi-empirical models used, the best fit was obtained for three models named *Modified Henderson–Pabis*, *Henderson–Pabis*, and *Two Term*. The comparison of these models with the proposed new model, ANN, and ANFIS, based on R^2 and RMSE values, confirmed that the kinetic drying data were perfectly described by the latter three models. The proposed model, ANN, and ANFIS were closer to each other by the R^2 and RMSE epochs. The proposed model used fewer epochs (4 epochs) than the other models, indicating that this model would be more applicable in agri-food industries.

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List of abbreviations and symbols

ANFIS	– adaptive neural-fuzzy inference system
ANN	– artificial neural networks
EPM	– prediction error model
MAE	– mean absolute error
MR	– moisture ratio
R	– correlation coefficient
R^2	– determination coefficient
R^2_{adj}	– adjusted coefficient
RMSE	– root mean square error
χ^2	– reduced chi-square

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SAŽETAK

Umjetna inteligencija i matematičko modeliranje kinetike sušenja prethodno obrađenih cjelovitih plodova marelice

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Ovim istraživanjem obuhvaćeno je praćenje i modeliranje kinetike sušenja cjelovitih plodova marelice prethodno obrađenih otopinama saharoze, natrijeva klorida i natrijeva bisulfita. Sušenje je provedeno u mikrovalnoj pećnici pri različitim snagama (200, 400 i 800 W). Za predviđanje vremena sušenja (*DT*) i omjera vlage (*MR*) primijenjena su dva modela umjetne inteligencije: umjetna neuronska mreža (ANN) i prilagodljivi sustav neizrazitog zaključivanja zasnovanog na neuronskoj mreži (ANFIS). S druge strane, za predviđanje *MR*-a upotrijebljeno je 20 postojećih poluempirijskih modela te jedan koji su autori izradili sami. Rezultati su, kod sve tri primijenjene obrade, pokazali redukciju vremena sušenja s povećanjem snage mikrovalne pećnice. Tretman otopinom natrijeva klorida pokazao se najpogodnijim. Koeficijenti korelacije ANN modela za vrijeme sušenja (0,9992) i omjer vlage (0,9997) bili su viši nego kod ANFIS modela (0,9941 i 0,9995). Za dvadeset primijenjenih polu-empirijskih modela, tri modela pokazala su se podudarnim s rezultatima ovog istraživanja (*modificirani model Hendersona i Pabisa*, *model Hendersona i Pabisa* te *model dvaju pojmova*). Uspoređujući tri spomenuta modela i model predložen u ovom radu, kao i predviđanje *MR*-a ANN-om, uočeno je da je model predložen u radu najprikladniji za opisivanje kinetike sušenja marelice tretirane otopinom natrijeva klorida. Takvi rezultati ukazuju da bi se predloženi model potencijalno mogao ubuduće primjenjivati za simulaciji kinetike sušenja voća i povrća.

Ključne riječi

Marelica, kinetika sušenja, mikrovalna pećnica, modeli, ANN, ANFIS

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