PREDICTION OF PADDY DRYING KINETICS IN AN IR ASSISTED HOT-AIR DRYER USING ANN AND ANFIS

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Accurate modelling of the drying process of agricultural material is an essential step toward the development of advanced drying monitoring and control systems. In this study, Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and mathematical modelling were employed to predict the moisture ratio of paddy during the drying process in a combined hot air IR-assisted dryer in fixed and vibratory bed modes. The grains were dried as thin layers at three infrared power levels of 50, 100 and 150 W and temperature levels of 40, 50 and 60 °C. The simulation results proved that The ANN model with 3-18-16-1 topology, LM training function, logarithm sigmoid transfer function in the first, and tangent sigmoid transfer function in the second hidden layer was the most accurate model. The R^2, RMSE and MAE values for the ANN model in the fixed-bed mode were 99.92%, 0.0037 and 0.0026, respectively. These values for vibratory mode were 99.94%, 0.0030 and 0.0021, respectively. It was concluded that ANN and ANFIS models were more appropriate tools than mathematical models for predicting the hot air-IR drying kinetics of paddy.

artificial intelligence, drying, infrared, modeling, paddy

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INTRODUCTION

Drying (dehydration) is one of the oldest and most vital operations of crops and food preservation. During the drying process, a large amount of water is evaporated from the material, and the moisture content will be in equilibrium with normal atmospheric air or to such a quantity that minimizes the water activity, fungi and microorganisms. The final moisture content varieties and depend on the material (Chen, Mujumdar, 2014). Drying is a complex process with simultaneous, and often coupled and multi-phase transfer of heat, mass and momentum (Yilbas et al., 2003). The main goal of this process is to increase the shelf life of foods by reducing water activity, guaranteeing product stability and minimizing packaging requirements (Movagharnejad, Nikzad 2007, Fellows, 2009).

Rice (*Oryza sativa L.*) is one of the most critical commercial cereals and food crops that is widely consumed as a staple food by a large part of the world's population, especially in Asia and Africa. According to the FAO statistics, the annual world production of rice was about 996 million tons in 2018, and about 90% of this production takes place in Asia (FAOSTAT, 2019).

Rice is the second most important cereal after wheat in Iran, where it is mostly cultivated in Mazandaran and Guilan provinces, with about 600,000 hectares area under cultivation, which produces more than 75% of the total rice crop in the country (Mehran et al., 2019).

Rice is harvested as paddy at 18-24% (w.b.) moisture content depending on the rice cultivar, growth location, number of cutting, and harvesting methods (Brooker et al., 1992; Nosrati et al., 2019). For the safe storage and prevention of paddy spoilage due to high initial moisture content, it must be dried to the moisture content of about 12-14% on a wet basis (P a n et al., 2008). Thus, drying unit operation has become a necessary part of paddy post-harvest in the rice processing factories.

According to the literature, there are over 400 types of dryers were reported (M u j u m d a r , 1997) and new drying methods have been introduced replacing traditional dryers in recent years. One of these techniques is infrared (IR) drying, which many researchers have begun using for drying agricultural products (S h a r m a et al., 2005; K o c a b i y i k , T e z e r , 2009). Research on this technology and other new drying procedures is an ongoing process (d e O l i v e i r a et al., 2020; X i et al., 2020).

Infrared radiation (IR) is a part of the electromagnetic spectrum with a wavelength range of 0.75 to 1000 μm. The IR band can be divided into three regions of near-IR (0.75-3), mid-IR (3-25) and far-IR (25-1000) radiation (S a k a i , H a n z a w a , 1994). The wavelengths between 2.5 to 200 μm are usually used for drying purposes (P a n , A t u n g u l u , 2010). During the IR drying, the water in the product is evaporated by absorbing infrared radiation from the heating elements without heating the surrounding air (M o h s e n i n , 1984; J o n e s , 1992). This drying technology has several advantages, such as simplicity of the equipment, uniform heating, high-quality dried materials, reduced drying time, no pollution and significant energy saving (T o ğ r u l , 2006; M o t e v a l i et al., 2011). According to the literature, paddy can be dried by different dryers such as fluidized- bed (S a r k e r et al., 2015; C h o k p h o e m p h u n , C h o k p h o e m p h u n , 2018), microwave (Jafari et al., 2018), and IR (N o s r a t i et al., 2019). As reported by Z a r e et al. (2015), the IR drying method is an appropriate method for heat-sensitive agricultural materials like paddy. The IR technology can be assisted with hot air dryers. A combined IR-hot air drying system has advantages such as higher quality of dried material and shorter drying time compared to IR or hot air, separately. In addition, energy consumption is dramatically reduced, and heat and mass can transfer more efficiently (Ł e c h t a ń s k a et al., 2015).

Several studies have been carried out on IR drying of agricultural crops such as vegetables (H e b b a r et al., 2004), onions (P r a v e e n K u m a r et al., 2005), kiwifruits (A i d a n i et al., 2017; S a d e g h i et al., 2019), banana slices (N i m m o l et al., 2007), green pea (B a r z e g a r et al., 2015), spearmint (N o z a d et al., 2016), and rough rice (Z a r e et al., 2015). A good and informative review of the applications of IR drying systems is provided by P a w a r , P r a t a p e (2017).

One of the challenges in the IR-drying of agricultural grains is that the bulks of grains do not dry uniformly as the IR source transfers the energy directly to the product surface, and the closer layers to the surface are dried more, compared to the layers deep inside the paddy bed. The vibration of the drying chamber can agitate the product, resulting in more homogenous dehydration and improved quality of the dried product. A laboratory-scale vibration aided infrared dryer was developed by D a s et al. (2004) to investigate the drying characteristics of paddy. They reported that the Page model adequately fitted the experimental drying data. In a similar study, by conducting experimental tests in a combined IR-vibration dryer, it was concluded that the radiation intensity and the depth of the drying bed were crucial parameters of the drying rate of paddy (D a s et al., 2009). In another study, hot-air infrared drying of corn in a vibratory bed was investigated. The researchers perused characteristics of thin layer drying of the product experimentally, and finally appropriate mathematical drying model was presented based on IR- intensity and temperature (R a h m a n i a n - K o u s h k a k i et al., 2017).

Nowadays, artificial intelligence (AI) methods such as artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) are widely used in many agricultural products, like predicting drying characteristics during the dehydration process.

ANN is a massive parallel-distributed information processing system developed as a generalized mathematical model of human brain activities. The requirements of this approach are only expressions and inputs-output relationships about the nature of the phenomenon, and items such as assumptions and predefined mathematical relationships are not required. ANN is a suitable method for modelling complex and non-linear industrial processes.

ANFIS is a synergic hybrid combination of ANN, and a fuzzy inference system (FIS) used to solve complex and high non-linearity problems. It is based on the input-output data pairs of the system under consideration (B u r a g o h a i n , M a h a n t a , 2008).

Empirical correlations are usually accurate enough for each specific experiment, but these equations are not valid for other conditions. In other words, the development of generalized experimental equations is difficult and complex. In these situations, AI methods are good tools for dynamic modelling. In recent years, extensive agricultural research has been carried out on food processing modelling using ANN and ANFIS methods. ANN is the most widely used method for predicting the drying characteristics of commodities (C h o k p h o e m p h u n , C h o k p h o e m p h u n ,2018).

G o l p o u r et al. (2018) used the ANN model for predicting the moisture content of paddy dried in a fluidized-bed dryer, and an optimal model was obtained. They claimed that the ANN model was a proper method for predicting the moisture content of paddy.

ANN's approach with different architects was used by M a h j o o r i a n et al. (2017) to estimate the moisture ratio of kiwi slices. They reported that the ANN with a sigmoid logarithm activation function containing 13 neurons in the first and second hidden layers was able to successfully predict the moisture ratio with good accuracy.

In another study conducted by K a v e h et al. (2018), the drying characteristics of three agricultural products (potato, garlic and cantaloupe) during the convective hot air drying were investigated using ANN and ANFIS methods. The results revealed that the ANFIS method is more capable than the ANN model in evaluating outputs.

The applications of some AI methods for many aspects of agricultural products have been investigated by B a l i , S i n g l a (2022). It was demonstrated that the ANFIS model performs appropriately in various agri-food systems (B a k h s h i p o u r , Z a r e i f o r o u s h , 2020), and this technique can be applied to research related to postharvest technology with satisfactory results. B a k h s h i p o u r et al. (2021) employed ANFIS methods for predicting stevia leaves' drying time and moisture ratio by hot air-infrared drying technique. They concluded that the ANFIS approach could give a good estimation of the drying kinetics of the product in an infrared-assisted hot-air dryer.

However, to the best of our knowledge, little information is available for combined infrared-assisted vibratory-bed drying of paddy (D a s et al., 2004; D a s et al., 2009). Furthermore, no report related to the capability of intelligent modelling is available for predicting paddy drying kinetics in these types of dryers. As a novelty, the present study tries to fulfil this shortage. The first aim was to investigate the use of mathematical models for describing paddy drying kinetics in a hybrid drying system of hot air, IR and vibratory in different experimental conditions. Also, the ability of ANNs and ANFIS methods to depict the drying behavior of paddy in the above-mentioned hybrid dryer was investigated.

MATERIAL AND METHODS

Raw material preparation

To perform drying experiments, freshly harvested paddy of the Fajr cultivar was selected and procured from a local farm near Rasht City, Iran. The samples were completely cleaned of foreign materials and immature grains, then sealed in polyethylene bags and stored in a refrigerator at $4-5^{\circ}\mathrm{C}$. Approximately one hour before each test, samples were put out to adapt to the ambient temperature (M e h r a n et al., 2019).

The standard hot oven method was used to measure the kernels' average initial moisture content. On this basis, three paddy samples were taken in aluminum boxes and kept in a hot-air oven at $103^{\circ}\mathrm{C}$ for 24 hours (S t a n d a r d s , 2016). The initial moisture content of the paddy was determined as 0.24 (kg matter/kg wet matter).

Experimental test-rig

A schematic of this drying system is presented in Fig 1. The dimension of the main chamber was 70×70×75 cm. The dryer mainly consisted of three units of convective hot air, IR and vibration, which could work separately and in different combinations.

Hot air heating unit

By using an inverter (LS, SV040iG5-4, Korea) controlled centrifugal blower, the produced heat of the electrically heated element (two elements with a nominal power of 1 kW) was conveyed to the drying chamber through a deformable tube having a diameter of 20 cm.

To perform a uniform airflow, a perforated tray with dimensions of 50×50 cm was used on which the paddy samples were placed. A conical inlet (with an angle of about 100º) was used to distribute the inlet air below the drying bed. The air velocity for all tests was measured by TESTO 425 hotwire. The air velocity was 0.15 m/s (S t a n d a r d , 2003). The tray was divided into four parts. A basket containing paddy kernels in a thin layer form was placed in each part, and to control and keep the inlet drying air temperature constant, a thermostat was used in this unit.

Infrared heating unit

The infrared radiation sources were placed on the upper side of the dryer. This dryer consisted of four infrared lamps (Noor lamp co, Iran) with a nominal power of 250 W. The vertical distance of the lamps to the paddy surface was adjusted to about 20 cm.

The output radiation intensity was varied by regulating the electrical power input to the lamps. A rotational

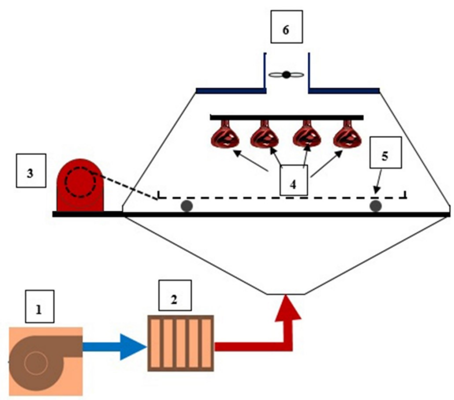

Fig. 1. A Schematic of the experimental test-rig drying system; 1. Centrifugal blower; 2. Heater; 3. Electromotor; 4. IR lamps; 5. Perforated tray; 6. Outlet gate

Table 1. Evaluated mathematical models used for kinetic drying

Model no.	Model Name	Model Equaition	Reference
1	Wang and Singh	MR = a t^2 + b t + c	Wang and Singh (1978)
2	Henderson and Pabis	MR = a exp(– k t)	Henderson and Pabis (1961)
3	Logarithmic	MR = a exp(– k t) + c	Henderson (1974)
4	Page	MR = a exp(– k t^n)	Diamante and Munro (1993)
5	Newton	MR = exp (– k t)	O'Callaghan et al. (1971)

potentiometer and a digital multimeter (TES Model 232, Taiwan) were used to set the input electric power of the lamps to zero, 50 W, 100 W and 150 W.

Vibration unit

The vibration unit mainly comprised an electromotor (550 W, DC), a crankshaft, and a connecting rod. The motor is equipped with a collar having an eccentricity of 20 mm to convert the rotation of the electromotor shaft to reciprocating motion to vibrate the drying bed horizontally. The frequency of the electric motor was adjusted using an inverter (LS, SV040iG5-4, Korea) to obtain the reciprocating motion of the sample tray. According to the literature and different trials and errors, the appropriate frequency of vibration motion was set to 20 Hz.

Experimental procedure

The experiments were conducted in the Renewable Energy Research Center of the Department of Biosystems Engineering, University of Guilan, Rasht, Iran. Before each test, the dryer was run without a sample for about 15 min to set the desired steady-state condition. The influences of radiation intensity (0, 50, 100, and 150 W) and air temperature (40, 50 and 60ºC) in two modes of fixed and vibration bed dryers on the moisture ratio of paddy were investigated. The experiments were carried out until the ultimate moisture content of the paddy was reduced to 0.14 (kg water/kg wet matter). During the tests, the thickness of the paddy layer was about (3 mm). An electronics scale (GX-1000, A&D Co., Japan) with an accuracy of 0.001 g was used to measure moisture content variation during drying. It should be noted that the tests were done in three replications.

Drying kinetics

Table 1 consists of five mathematical equations which representing the moisture ratio (MR) as a function of time. The models have been used to fit empirical correlations for the experimental data.

The moisture ratio can be calculated using Eq.1.

$$MR = \frac{M - M_o}{M_o - M_\epsilon} \tag{1}$$

The value of equilibrium moisture content is usually small relative to and (Doymaz, Pala, 2002). Thus, Eq.1 may be simplified to Eq.2, which is commonly used for MR calculation in grain drying studies (Rahmanian-Koushkaki et al., 2017; Mehran et al., 2019)

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

The non-linear regression procedure was used to obtain constants of mathematical models. For all runs, the curve fitting toolbox of MATLAB software was performed. Three statistical criteria, including coefficient of determination (R^2), chi-square (χ^2) and root mean squared error (RMSE), were used to select the best model in each experimental condition (Eq.3 to Eq.5):

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{N}(x_{exp,i} - x_{pred,i})^2}{\sum_{i=1}^{N}(x_{exp,i} - \overline{x_{exp}})^2}\right] \tag{3}$$

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(x_{exp,i} - x_{pred,i})^2\right]^{0.5} \tag{4}$$

$$\chi^2 = \frac{\sum_{i=1}^{n}\left(x_{exp,i} - x_{pre,i}\right)^2}{N - n} \tag{5}$$

where $x_{exp,i}$ and $x_{pred,i}$ are the ith experimental and predicted MR data from N total MR values, respectively. $\overline{x_{exp}}$ is the average of experimental MR values and n is the number of constants in drying models. The model with the highest value of R^2 and the least values of χ^2 and $RMSE$ is the suited model for describing the drying kinetics of paddy.

Artificial neural networks (ANN)

Different topologies of multilayer feed-forward back-propagation neural networks with one or two hidden layers and different numbers of neurons in each hidden layer (1 neuron to 20 neurons) were evaluated for predicting the MR of paddy during drying under IR-assisted fixed-bed and vibratory-bed conditions. Two types of transfer functions, including Tangent-sigmoid and logarithm-sigmoid ('*tansig*' and '*logsig*' codes in MATLAB, respectively), were applied in the hidden layers of the ANNs. The transfer function of the output

Table 2. Different parameters and relevant values that used for constructing ANFIS models

Number of MFs	Optimization Method	Input MF	Output MF
2-2-2	Backpropagation	Gaussian	Constant
3-3-3		Sigmoid	
4-4-4	Hybrid	Triangular	Linear

layer was set to be pure-line. Values of drying time, inlet air temperature, and infrared radiation intensity were fed into the networks as input data, and the MR values were the target data. In a random mode, 60% and 20% of data were used as the training dataset and for cross-validation, respectively. The remaining 20% were used as model test datasets.

In the present study, Levenberg-Marquardt (LM) and Scaled Conjugate Gradient (SCG) training techniques (‘*trainlm*’ and ‘*trainscg*’ codes in MATLAB, respectively), which are the most common training methods in agricultural studies (Pandey et al., 2010; Kamble et al., 2015; Taheri-Garavand et al., 2018), were applied as the ANN training function. A schematic architecture of the developed ANNs with two hidden layers is presented in Fig. 2a.

Adaptive network-based fuzzy inference system (ANFIS)

The capability of Sugeno ANFIS models was also investigated in this study to predict paddy MR based on three variables drying time, inlet drying air temperature, and infrared radiation intensity. A schematic representation of ANFIS architecture is shown in Fig. 2b. The data were split randomly into 60%, 20%, and 20% percent sets employed for the training, validation, and testing phases.

Different structures of neuro-fuzzy modelling systems were developed and evaluated. Type of input and output Membership Functions (MFs), Number of MFs, and the Optimization Method (OM) were the parameters that were adjusted and evaluated to obtain the desired performance. The membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1, called the degree of membership (Adnan et al., 2015). Three different input MFs, namely Gaussian, Sigmoidal, and Triangular MFs, were studied. Descriptions of these MFs are presented in the literature (Yılmaz, Arslan, 2008; Paluszek, Thomas, 2019). The two output MFs applied in this study were linear and constant MFs, which have been used in previous agricultural-related fuzzy-system development research (Ahmadaali et al., 2013; Amiri, Shabani, 2017; Shafaei et al., 2019).

The OMs adjust membership function parameters to follow the training data (Kau, Aggrarwal, 2013). In this study, two OMs were investigated: Back-Propagation (BP), in which the error rates propagate backward and the premise parameters are updated by the gradient descent method, (Tashtoush et al., 2011), and the hybrid OM, which uses a combination of least squares and back-propagation methods to optimize the prediction (Kharb et al., 2014). The

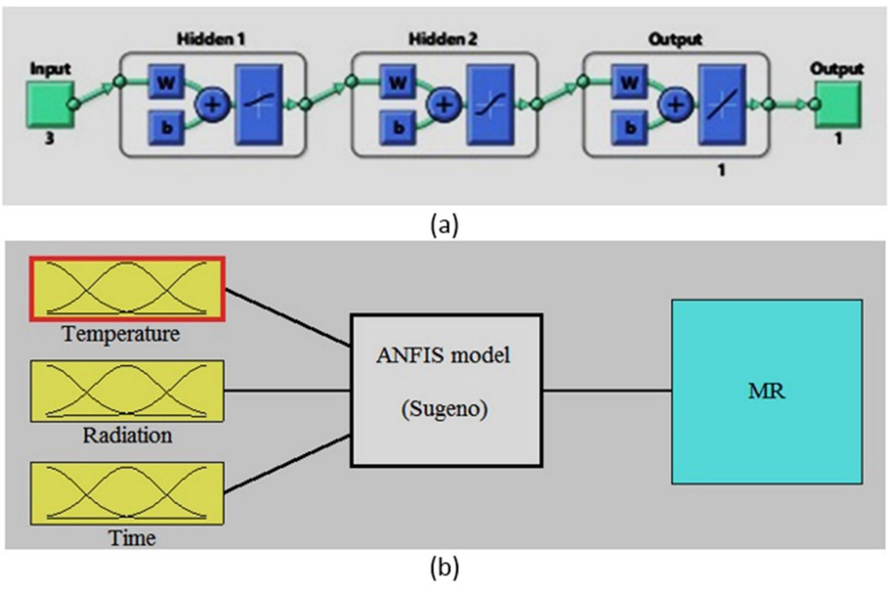

Fig. 2. The overall form of ANN (a) and ANFIS (b) model for prediction of MR during IR-assisted paddy drying (from MATLAB software)

Table 3. Values of coefficients of selected models and statistical criteria at different temperatures and radiation intensities during drying in IR-fixed mode

T (°C)	IR power (W)	Best Model	Model criteria			Model parameters*				
			R2	χ2	RMSE	a	b	c	K	n
40	0	Page	0.9951	0.0035	0.0084	--	--	--	0.0259	0.6019
	100	Logarithmic	0.9990	0.0005	0.0045	0.5083	--	0.4874	0.0199	--
	150	Page	0.9995	0.0003	0.0030	--	--	--	0.0333	0.6957
	200	Wang and Singh	0.9963	0.0017	0.0090	0.0002	-0.0198	0.9959	--	--
50	0	Page	0.9977	0.0012	0.0061	--	--	--	0.0264	0.6575
	100	Logarithmic	0.9953	0.0023	0.0105	0.5364	--	0.4605	0.0253	--
	150	Page	0.9952	0.0021	0.0097	--	--	--	0.0365	0.7663
	200	Page	0.9985	0.0006	0.0058	--	--	--	0.0335	0.844
60	0	Page	0.9985	0.0007	0.0054	--	--	--	0.0294	0.6817
	100	Page	0.9991	0.0004	0.0042	--	--	--	0.0423	0.7328
	150	Page	0.9969	0.0011	0.0084	--	--	--	0.0486	0.7620
	200	Page	0.9995	0.0002	0.0034	--	--	--	0.0348	0.9456

* The a, b, c, k, and n values are the constant values of the best fitted mathematical models, according to Table 1.

number of MFs was selected to be 2-2-2, 3-3-3, and 4-4-4. Table 2 lists a summary of the studied ANFIS parameters, which generate thirty-three combinations (3 Number of MFs × 2 OMs × 3 Input MFs × 2 Output MFs = 36 structures) in this study.

The developed ANN and ANFIS models were evaluated based on three statistical parameters, namely, R^2, RMSE and Mean Absolute Error (MAE). These criteria were calculated using equations 3, 4 and 6 (Tao et al., 2016; Bakhshipour et al., 2018):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|x_{exp,i} - x_{pred,i}\right| \qquad (6)$$

where $x_{exp,i}$ and $x_{pred,i}$ are the ith experimental and predicted MR data from N total MR values, respectively. The models with the highest R^2, the least RMSE, and MAE were selected as the most precise MR predictors.

RESULTS AND DISCUSSION

Drying kinetics

The effect of drying conditions on the drying overall time is presented graphically in Fig. 3. It can be

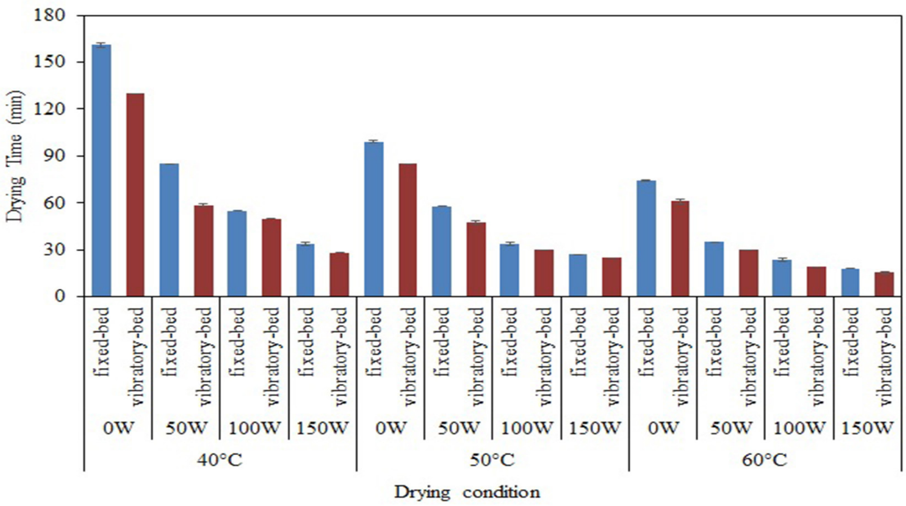

Fig. 3. Averages of overall drying time of paddy in different drying condition

Table 4. Values of coefficients of selected models and statistical criteria at different temperatures and radiation intensities during drying in IR-vibratory mode

T (°C)	IR power (W)	Best Model	Model criteria			Model parameters*				
			R2	χ2	RMSE	a	b	c	k	n
40	0	Logarithmic	0.9976	0.0021	0.0066	0.4314	--	0.5543	0.0216	--
	100	Page	0.9957	0.0021	0.0086	--	--	--	0.0344	0.6789
	150	Logarithmic	0.9992	0.0004	0.0038	0.4851	--	0.5122	0.0392	--
	200	Page	0.9998	0.0001	0.0022	--	--	--	0.0280	0.8911
50	0	Page	0.9986	0.0009	0.0050	--	--	--	0.0283	0.6727
	100	Page	0.9986	0.0009	0.0050	--	--	--	0.0283	0.6727
	150	Page	0.9997	0.0001	0.0023	--	--	--	0.0408	0.7629
	200	Page	0.9983	0.0006	0.0060	--	--	--	0.0416	0.7907
60	0	Logarithmic	0.9974	0.0013	0.0069	0.4899	--	0.5046	0.0294	--
	100	Page	0.9962	0.0015	0.0088	--	--	--	0.0477	0.7164
	150	Wang and Singh	0.9995	0.0002	0.0036	0.0008	-0.0368	0.9990	--	--
	200	Wang and Singh	0.9977	0.0008	0.0087	0.0007	-0.0379	0.9998	--	--

* The a, b, c, k, and n values are the constant values of the best fitted mathematical models, according to Table 1.

Table 5. Performance criteria of the most accurate ANN structures for MR prediction in IR-assisted fixed-bed paddy drying

Training function	Transfer functions in hidden layer		Topology	R^2 (%)	*RMSE*	*MAE*
	Layer 1	Layer 2				
trainlm	Tansig	-	3-16-1	99.84	0.0053	0.0041
	Logsig	-	3-17-1	99.86	0.0049	0.0035
	Tansig	Tansig	3-20-11-1	99.90	0.0043	0.0027
	Tansig	Logsig	3-14-15-1	99.92	0.0041	0.0024
	Logsig	Logsig	3-16-13-1	99.92	0.0040	0.0024
	Logsig	*Tansig*	*3-18-16-1*	*99.92*	*0.0037*	*0.0023*
trainscg	Tansig	-	3-16-1	99.56	0.0089	0.0070
	Logsig	-	3-14-1	99.18	0.0120	0.0090
	Tansig	Tansig	3-13-19-1	99.80	0.0061	0.0044
	Tansig	Logsig	3-16-8-1	99.76	0.066	0.0049
	Logsig	Logsig	3-15-4-1	98.90	0.0137	0.0116
	Logsig	Tansig	3-11-10-1	99.64	0.0080	0.0060

observed that for each couple of inlet air temperature and IR power, the overall drying time decreases when vibration is applied to the drying bed. This means that the dryer's working capacity can improve by using the vibratory-bed mode. Increasing the inlet air temperature and IR power can also increase the drying rate and decrease overall drying time.

Different mathematical models were used to fit the drying trend of paddy at different conditions. The calculated constants of each mathematical model and values of statistical criteria are presented in Tables 3 and 4 for fixed and vibratory modes, respectively. The tables also show that almost all the five selected models provide a good description of the experimental drying data of paddy. A comparison of the selected models shows that the Page model was the most precise mathematical model, which satisfactorily described the drying behaviour of the paddy grains in most drying conditions. For 16 of the 24 different drying conditions (12 cases for fixed-bed and 12 cases for vibratory-bed mode), the Page model was the most appropriate predictor (R^2 range from 0.9951 to 0.9998).

Obviously, there is no general empirical model for a range of drying parameters, and in addition, using empirical models to correlate drying kinetics is very time-consuming. Since mathematical drying correlations are limited to one specific experiment, different mathematical models are fitted to different conditions. In contrast, a unique ANN or ANFIS model gives better results for each experiment.

Table 6. Performance criteria of the most accurate ANN structures for MR prediction in IR-assisted vibratory-bed paddy drying

Training function	Transfer functions in hidden layer		Topology	R^2 (%)	*RMSE*	*MAE*
	Layer 1	Layer 2				
trainlm	Tansig	-	3-19-1	99.89	0.0047	0.0033
	logsig	-	3-16-1	99.91	0.0042	0.0031
	Tansig	Tansig	3-19-14-1	99.94	0.0031	0.0022
	Tansig	logsig	3-18-16-1	99.94	0.0032	0.0023
	logsig	logsig	3-17-16-1	99.94	0.0031	0.0023
	logsig	*tansig*	*3-20-16-1*	*99.94*	*0.0030*	*0.0021*
trainscg	Tansig	-	3-14-1	99.56	0.0092	0.0073
	logsig	-	3-11-1	99.22	0.0116	0.0084
	Tansig	tansig	3-14-14-1	99.78	0.0062	0.0046
	Tansig	logsig	3-19-10-1	99.82	0.0056	0.0045
	logsig	logsig	3-18-5-1	99.62	0.0083	0.0062
	logsig	tansig	3-20-9-1	99.76	0.0063	0.0051

ANNs results

The most accurate MR predictor ANNs in each combination of transfer functions in hidden layers were selected based on the training performance criteria and are shown in Tables 5 and 6 for fixed and vibratory-bed drying conditions, respectively. Regarding performance criteria, the most precise ANN had the topology of 3-18-16-1, LM training function, logarithm sigmoid transfer function in the first layer, and tangent sigmoid transfer function in the second hidden layer. This structure's R2, RMSE, and MAE values were 99.92%, 0.0037, and 0.0026, respectively, for the training dataset. While similar R^2 values were obtained by two other ANN structures and the most successful ANN was selected based on the lowest value of RMSE and MAE. The selected structure was able to predict MR values in the dataset with criteria of 99.58%, 0.0119 and 0.0101 for R^2, RMSE and MAE, respectively.

In the case of vibratory bed drying condition, among several ANNs having the highest R^2 (99.94%), the most reliable one, which was selected based on the lowest values of RSME (0.0030) and MAE (0.0021) values, had 3-20-16-1 topology, LM training function, logarithm sigmoid transfer function in the first layer, and tangent sigmoid transfer function in the second hidden layer. This model's R2, RSME, and MAE criteria in the test dataset were 99.71%, 0.0076, and 0.0077, respectively. ANN resulted in more accurate predictions for vibratory-bed drying than fixed-bed drying.

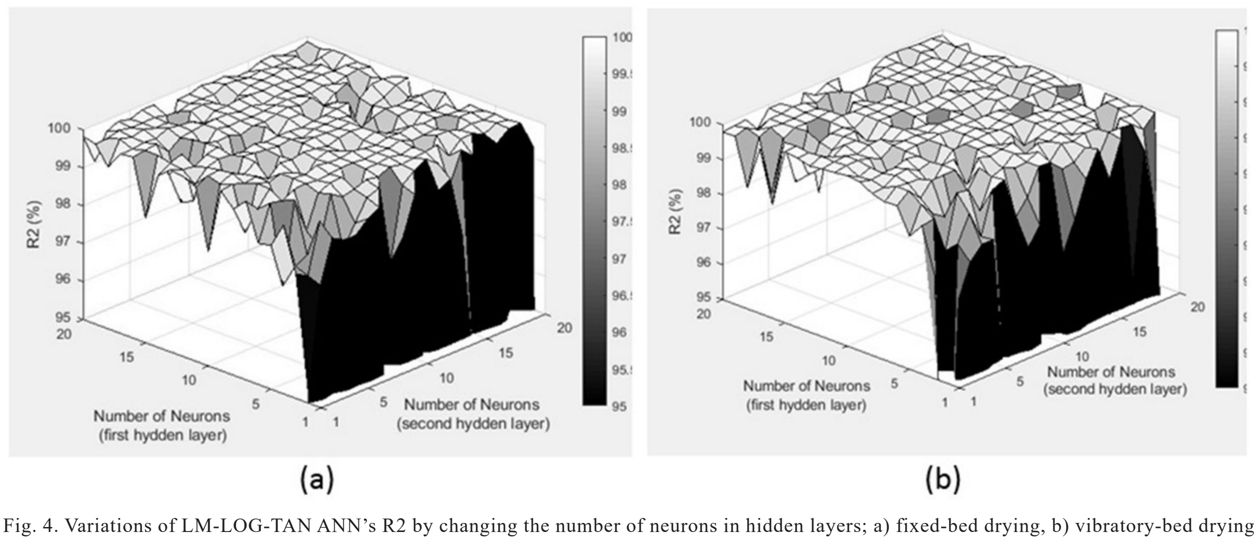

Fig. 4. Variations of LM-LOG-TAN ANN's R2 by changing the number of neurons in hidden layers; a) fixed-bed drying, b) vibratory-bed drying

Table 7. Performance criteria of the most accurate ANFIS structures for MR prediction in IR-assisted fixed-bed paddy drying

Number of MFs	Optimization Method	Input MF	Output MF	R^2 (%)	RMSE	MAE
2-2-2	Backpropagation	Triangular	Constant	92.90	0.0354	0.0396
2-2-2	*Hybrid*	*Gaussian*	*Linear*	*99.38*	*0.0105*	*0.0117*
2-2-2	Hybrid	Sigmoid	Linear	96.92	0.0233	0.02404
2-2-2	Hybrid	Triangular	Constant	92.90	0.0354	0.0391
2-2-2	Hybrid	Triangular	Linear	99.52	0.0092	0.0099
3-3-3	Backpropagation	Triangular	Constant	95.62	0.0278	0.0316
3-3-3	Hybrid	Sigmoid	Linear	99.40	0.0103	0.01065
3-3-3	Hybrid	Triangular	Constant	96.01	0.0265	0.0298
3-3-3	Hybrid	Triangular	Linear	99.78	0.0062	0.0060
4-4-4	*Hybrid*	*Gaussian*	*Linear*	*99.81*	*0.0058*	*0.0052*
4-4-4	Hybrid	Sigmoid	Constant	99.30	0.0111	0.0118
4-4-4	Hybrid	Triangular	Constant	92.43	0.0397	0.0362
4-4-4	Hybrid	Triangular	Linear	99.80	0.0060	0.0058

Overall, the LM training function, logarithm sigmoid transfer function in the first layer, and tangent sigmoid transfer function in the second layer (LM-LOG-TAN) have resulted in the most accurate MR predictor ANNs model. Fig. 4a and Fig. 4b graphically represent the variations of training R^2 values of this structure by changing the number of neurons in the first and second hidden layers. It should be noted that, the R^2 values of less than 95.00% were truncated to better show the R^2 variations on the plot top surfaces. It can be seen in Fig 4 that most of the topologies LM-LOG-TAN have resulted in very high R^2 values. It is also obvious that the lower R^2 values were obtained when the number of neurons was less than 5 in the first hidden layer. In Fig. 5, the plot of experimental MR values vs. ANN estimated ones (test data) is shown for fixed and vibratory bed drying. The concentration of the data points near the unity slope line illustrates the promising ability of ANN models to predict MR.

ANFIS results

Table 7 shows the R^2, RMSE, and MAE values of the most precise ANFIS architectures for MR pre-

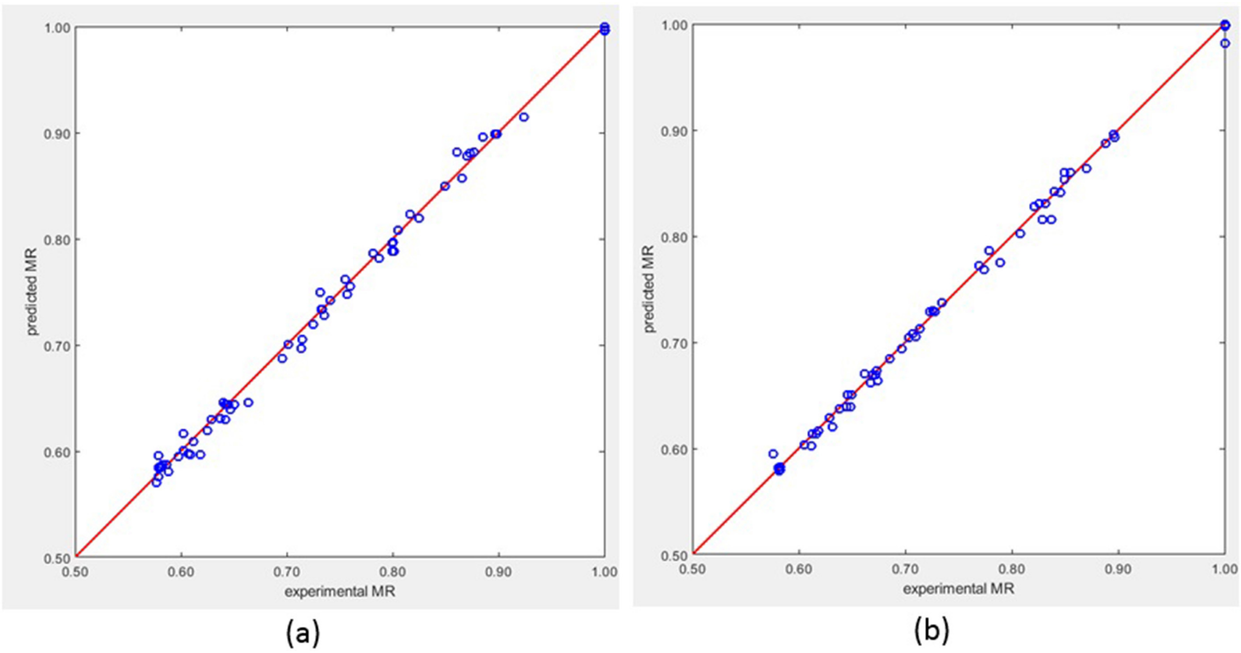

Fig. 5. Scatter plot of experimental vs. predicted MR values of ANN models for IR-assisted fixed-bed paddy drying (a) and vibratory-bed paddy drying (b)

Table 8. Performance criteria of the most accurate ANFIS structures for MR prediction in IR-assisted vibratory-bed paddy drying

Number of MFs	Optimization Method	Input MF	Output MF	*R2* (%)	*RMSE*	*MAE*
2-2-2	Backpropagation	Triangular	Constant	92.66	0.0363	0.0400
2-2-2	Hybrid	Gaussian	Linear	99.46	0.0098	0.0104
2-2-2	Hybrid	Sigmoid	Linear	96.77	0.0241	0.0251
2-2-2	Hybrid	Triangular	Constant	92.63	0.0363	0.0408
2-2-2	Hybrid	Triangular	Linear	99.80	0.0059	0.0061
3-3-3	Backpropagation	Triangular	Constant	95.18	0.0294	0.0318
3-3-3	Hybrid	Sigmoid	Linear	99.47	0.0098	0.0095
3-3-3	Hybrid	Triangular	Constant	95.54	0.0282	0.0301
3-3-3	*Hybrid*	*Triangular*	*Linear*	*99.89*	*0.0044*	*0.0042*
4-4-4	Hybrid	Gaussian	Constant	94.69	0.0308	0.0294
4-4-4	*Hybrid*	Gaussian	Linear	99.89	*0.0045*	*0.0045*
4-4-4	Hybrid	Sigmoid	Constant	97.47	0.0213	0.0282
4-4-4	Hybrid	Sigmoid	Linear	99.75	0.0067	0.0067
4-4-4	Hybrid	Triangular	Constant	97.36	0.0217	0.0226
4-4-4	Hybrid	Triangular	Linear	99.81	0.0059	0.0060

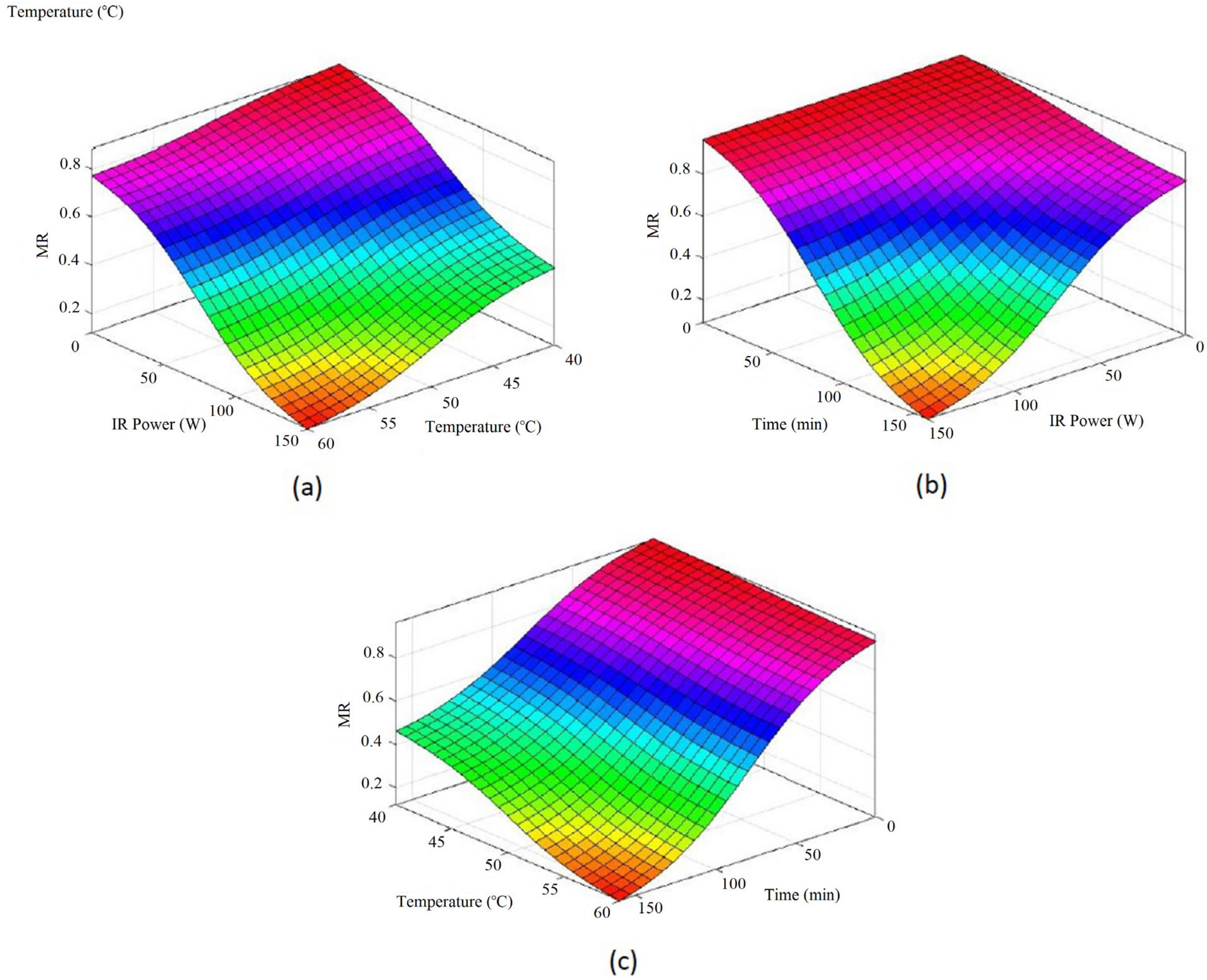

Fig. 6. The obtained HGL4-ANFIS surface plots for MR prediction of paddy during IR-assisted fixed-bed drying;
(a) MR vs. radiation and temperature, (b) MR vs. radiation and time, and (c) MR vs. time and temperature

diction in fixed-bed drying of paddy. The presented performance criteria in this table are obtained by evaluating the most accurate ANFIS models on the training dataset. The ANFIS model with the Hybrid optimization method, Gaussian input MF, Linear output MF, and 4-4-4 number of MFs (HGL4) was the most accurate model with R^2 of 99.81%. The RMSE and MAE values of this ANFIS structure were 0.0058 and 0.0052, respectively. This model's R2, RMSE, and MAE values were 99.35%, 0.0114, and 0.0105, while the model was evaluated using test data.

Also, going through Table 7, it is evident that, generally, ANFIS models with the hybrid optimization method were more successful than those with the back-propagation optimization method. The surface view of the obtained HGL4 fuzzy rules is shown in Fig. 6. This figure provides a 3-D view of the fuzzy model output (predicted MR) versus different combinations of the input variables. These surfaces are also good graphical presenters of the paddy drying behavior. For example, we can see in Figure 6c that the drying rate increases by increasing the inlet drying air from 40ºC to 60°C. In Fig 6, it can be perceived that by increasing the radiation and temperature, the slope of the MR reduction trend becomes steeper.

The most accurate model (HGL4) had 4-4-4 numbers of MFs. This means that there were 64 rules which ANFIS established to construct this precise MR prediction model. Such a number of rules seems almost impossible to develop by the expert. It shows the advantage of network-based fuzzy systems over conventional ones for decision-making on drying kinetics-related datasets. On the other hand, a large number of membership functions make it very difficult to interpret and apply the created rules for further works. From this point of view, the HTL2 (Hybrid-Triangular-Linear structure with 2-2-2 Number of MFs), which resulted in only 0.29% of R^2 lower than the HGL4 structure, by using only eight rules, is much simpler and more appropriate. The performance measures of HTL2 for the training dataset were 99.52%, 0.0092, and 0.0099 for R^2, RMSE, and MAE, respectively. This model's R2, RMSE, and MAE were 99.22%, 0.0128, and 0.0129, respectively.

The second, third, and fourth ranks of the most accurate ANFIS models belonged to those with hybrid optimization methods, triangular input MF and linear output MF, which shows the capability of this structure for prediction of MR in IR-assisted fixed-bed paddy drying. The R^2 values of this structure on the training dataset were 99.80%, 99.78%, and 99.52% when using 4-4-4, 3-3-3, and 2-2-2 membership functions, respectively.

Fig. 7 shows the scatter plot of measured MR values vs. those predicted by the HGL4 model (test dataset) for IR-assisted fixed-bed paddy drying. The concentration of the data points near the one-to-one line represents the perfect fit of the model-predicted data to the experimental ones.

Results of the most reliable ANFIS structures for predicting the MR during IR-assisted vibratory-bed drying of paddy are given in Table 8. In this case, the best performance criteria were obtained when a Triangular input MF, Linear output MF, Hybrid optimization method, and 3-3-3 number of MFs (HTL3) structure were used for MR prediction. The training performance criteria of the HTL4 structure were 99.89%, 0.0044, and 0.0042 for R^2, RMSE and MAE, respectively. The R^2, RMSE and MAE were 99.62%, 0.0086 and 0.0082, respectively, when the model was evaluated on the test dataset.

Also, as can be seen by examining Table 8, the structure of the HGL4 structure (Hybrid optimization method, Gaussian input MF, Linear output MF, and 4-4-4 membership functions) resulted in a similar R^2 with the HTL3 structure. Still, the HTL3 structure was selected for its lower values of RMSE (0.0045) and MAE (0.0045) rather than HGL4.

It should be noted that the best performance obtained by using the back-propagation optimization method belonged to the model with triangular input MF, Constant output MF and 3-3-3 membership functions (R^2 = 92.47%, RMSE = 0.0380 and MAE = 0.0374 on train dataset). Comparing these values with those achieved by the HTL3 structure shows that the hybrid optimization method is much more reliable than the back-propagation method for MR prediction during paddy drying.

As already observed in the case of the fixed-bed condition, all of the Hybrid-Triangular-Linear structures with different numbers of MF resulted in high prediction accuracies, which shows the significant

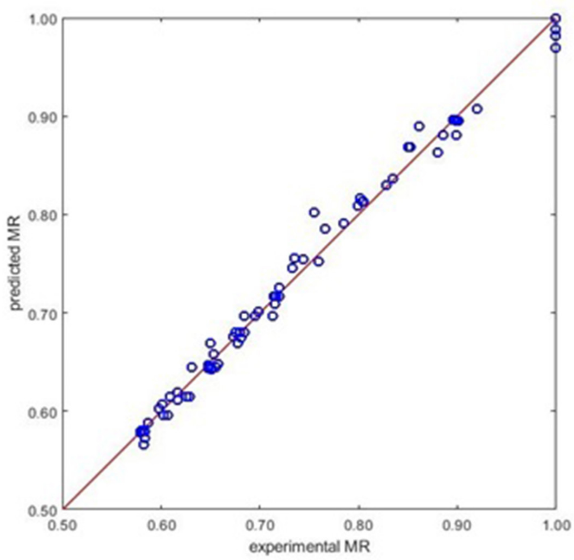

Fig. 7. Scatter plot of experimental vs. predicted MR values of HGL4 ANFIS model for IR-assisted fixed-bed paddy drying

reliability of this structure for monitoring the drying behavior of paddy.

The efficient applicability of ANFIS was reported by Ojediran et al. (2020) for predicting the MR of yam slices during drying in a convective hot air dryer with the R^2 and RMSE values of 0.98226 and 0.01702, respectively. The R^2 and RMSE values were reported to be 0.9998 and 0.0003, respectively, when the ANFIS system was used to fit the experimental MR data of almond kernels in a thin layer convection dryer with ultrasound pretreatment (Kaveh et al., 2018).

The membership surfaces of the HTL3 ANFIS model are demonstrated in Fig. 8. The general shape of this surface was almost similar to those presented in Fig. 6 for HGL4 ANFIS. However, the decreasing trends of surfaces in Fig. 8 are higher than those in Fig. 6. This shows that the vibratory-bed condition increased the drying rate of paddy compared with fixed-bed drying.

The scatter plot of experimental vs. HTL3-predicted MR values (test dataset) for IR-assisted vibratory-bed paddy drying is illustrated in Fig. 9. The points in this figure are closer to the one-to-one line than those in Fig. 7, which shows the higher prediction reliability of the fuzzy model for vibratory-bed data rather than fixed-bed data.

According to the results reported above, both ANN and ANFIS are robust and reliable methods for predicting the MR of paddy during the IR-assisted vibration drying process. The critical values of both models were found to be very high and very close to each other. However, the ANN predictors produced almost better results than the ANFIS ones, as the predicted MR values by the ANN were closer to the experimental data than the ANFIS models. Both models have been reported in the literature to work reliably for predicting the drying behavior of agricultural products in different drying methods (Ahmadaali et al., 2013; Kaveh, Amiri-Chayjan, 2015; Al-Mahasneh et al., 2016; Yousefi, 2017; Abbaspour-Gilandeh et al., 2020).

CONCLUSION

IR-hot air Hybrid drying of paddy kernels was conducted in an experimentally vibratory-bed dryer.

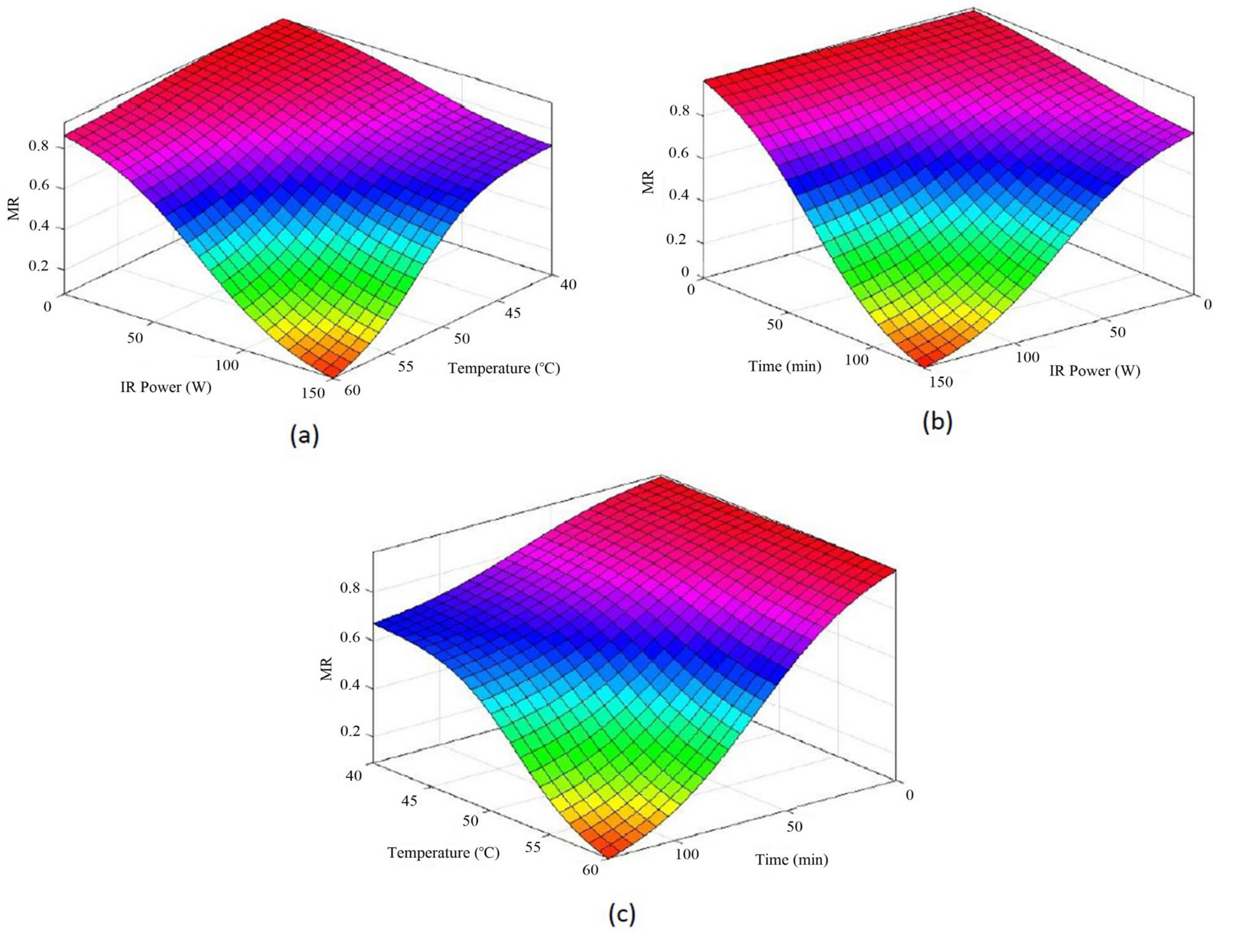

Fig. 8. The obtained HTL3-ANFIS surface plots for MR prediction of paddy during IR-assisted vibratory-bed drying;
(a) MR vs. radiation and temperature, (b) MR vs. radiation and time, and (c) MR vs. time and temperature

The effects of hot air temperature and radiation intensity on the paddy moisture ratio were investigated in fix-bed and vibratory-bed modes. It was observed that by using the vibratory-bed mode and increasing the inlet drying temperature and the IR lamp power, the drying time was reduced.

Different mathematical models were used to fit empirical correlations for the experimental data of paddy thin layer drying. The Page model was the most accurate mathematical MR predictor in most of the studied drying conditions, with an R2 of more than 0.995.

Two well-known AI methods (ANN and ANFIS) have been applied to predict the moisture ratio of the paddy. The results showed that both the ANN and ANFIS models were suitable for predicting the moisture ratio of grains, showing the advantage of neurocomputing methods for monitoring of paddy dryers. According to the statistical criteria, the ANN model was more accurate and efficient when compared with ANFIS. The best ANN models for predicting the MR had the topology of 3-18-16-1 and 3-20-16-1 for fixed and vibratory modes, respectively. In addition, using the LM training function, logarithm sigmoid transfer function in the first hidden layer, and tangent sigmoid transfer function in the second hidden layer have resulted in the most accurate MR predictor ANNs for both mentioned drying bed modes. Results showed that the optimized network for fix mode presented R^2 of 99.92%, RMSE of 0.0037 and MAE of 0.0026. These values were R^2=99.94%, RMSE=0.0030 and MAE=0.0021 for vibratory mode.

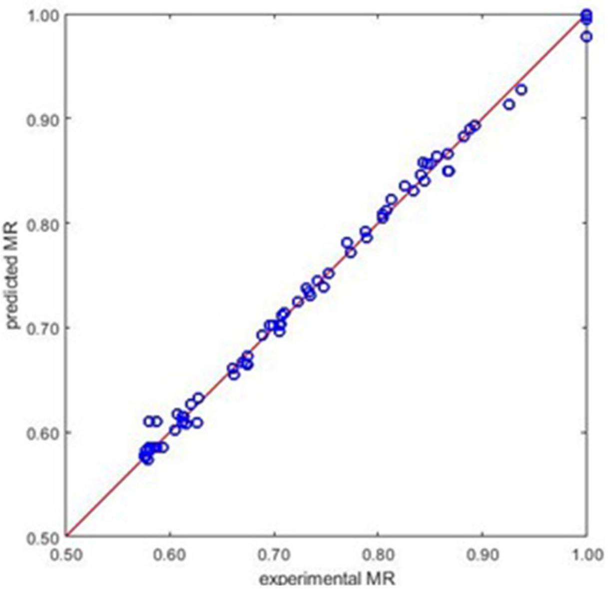

Fig. 9. Scatter plot of experimental vs. predicted MR values of HTL3 ANFIS model for IR-assisted vibratory-bed paddy drying

It can be concluded that the application of intelligent models, especially ANN, can be considered as an effective alternative method for monitoring paddy drying in IR-hot air hybrid dryers.

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