Generalization of drying kinetics during thin layer drying of paddy

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Abstract: Thin layer drying kinetic analysis of paddy dried under low temperature conditions (20 ℃-40 ℃), was carried out by using six different models. Among these models, Midilli model showed best fitted result with highest R2 and lowest RMSE and SSE values. It was observed that the drying rate constant k increased with the increase in drying temperature. For finding the effect of temperature, Midilli model was generalized by using two approaches namely globalization of drying rate constant and master curve technique. Master curve technique gave better fit with a R2 value of 0.998 than the global drying rate constant model. Further, artificial neural network (ANN) modeling was also used to model drying kinetics of paddy. Best architecture for the ANN modeling was 2-55-1, which showed the best performance than the other modeling techniques. An attempt of ANN-PSO approach was applied to develop a relationship between dependent variables i.e. critical drying temperature and independent variables namely drying temperature, time and moisture content in wet basis (% wb). Effective diffusivity of drying linearly increased with the increase in temperature. The value of activation energy of the paddy under investigation was 54.23 kJ/mol.

Keywords: master curve technique, ANN, thin layer drying, drying rate constant, ANN-PSO

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1 Introduction

Paddy is one of the most important crops in the world. Normally, paddy is harvested at high moisture content (usually in the range of 18%-26% wet basis (wb). It is very difficult to manage this highly moist paddy during harvesting periods (especially in Asian countries), as high moisture content instigates the excessive mold growth and high respiration rate from grain. As a result, dry matter is lost and rice yellowing takes place due to the liberated heat from respiration and other biological activities (Soponronnarit and Nathakaranakule, 1990). To prevent all the problems and to get high quality of paddy, the moisture content of paddy must be lowered down to 12%-14% wb (Soponronnarit & Preechakul, 1990).

Drying is one of the most important process in order to preserve the paddy for longer time and finally to get white rice. This process is energy intensive and significantly affects the quality of rice. Several drying techniques like low temperature continuous drying for long duration, high temperature drying for short time, thin layer multi-pass/intermittent drying, have been implemented in order to improve the rice quality. Factors like variety, harvesting methods, moisture content, drying methods and milling techniques play an important role in getting proper head rice yield (HRY) (Dung et al., 1980; Fan et al., 2000; Iguaz et al., 2003). Now-a-days high temperature drying technique is mostly used due to its fast drying rate. But it can deteriorate the grain quality if not conducted properly. If rapid cooling follows rapid drying, especially drying the grain rapidly from 19% to 14% moisture content, stress cracks tend to develop (Brook, 1988). In this way, improper drying condition leads to stress crack development, which can increase the

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number of broken rice. As broken rice decreases the market value, a proper drying process should be implemented for the paddy, so that we can have more amount of head rice yield with minimum energy input.

Few studies have been done related to the low temperature drying system and its advantageous capability to reduce the product quality deterioration during drying. Cihan et al. (2007 a, b) studied the intermittent thin layer drying behavior of rough rice at 40 ℃. Iguaz et al. (2003) studied that temperature had more impact on the thin layer drying constant than relative humidity (RH). It was also observed that under the low air temperature (<30 ℃), air velocity significantly influenced the drying constant. Kahveci et al. (2002) conducted a rough rice drying experiment under different drying condition and developed a theoretical drying model for predicting the drying kinetics of rough rice. It was also reported that temperature greatly influenced the rough rice drying. Basunia and Abe (1988) found that, for describing thin-layer drying characteristics of freshly harvested rough rice dried under natural convection with air temperature and RH ranging between 22.3 ℃-34.9 ℃ and 34.5%-57.9%, respectively and Page Equation is more suitable. Ondier et al. (2010) studied low temperature and low humidity drying of rough rice and observed that low temperature and low humidity had an adverse effect on the product quality. They found Page model as the best fitted model for describing the drying behavior of rough rice. Dung et al. (1980), Cihan (1991) and Jayas et al. (1991) have also reported the similar type of findings.

One of the most important factors in drying process is modeling and optimization. Various mathematical modeling techniques are used to develop relationship between the dependent and independent variables in case of drying process. Using the empirical equations is the simplest way to determine the drying characteristics. But this kind of correlation is based on a particular product. So, this approach generally fails to describe the exact drying behavior of agricultural products for a range of drying parameters (Movagharnejad and Nikzad, 2007). Analytical drying models can be used in order to solve the particular problem. But, these models are very difficult to use in actual drying system as these are composed of critical general solutions of simultaneous heat and mass transfer differential equations.

Nowadays, artificial neural network (ANN) models and master curve techniques are used for developing the relationship between moisture ratio and other independent variables in case of drying technology. Artificial neural network technique is a powerful technique for the analysis of nonlinear and multiple analysis system (Hua et al., 2011). It has the capability of learning complex non-linear relationship between the input and output variables of a system (Golpour et al., 2015). Its strength of learning capability increases gradually with the update of weight, which is the strength of the developed network. Many researchers have implemented ANN modeling for describing the drying behavior of various food particles (Murthy et al., 2013; Erenturk et al., 2007; Movagharnejad et al., 2007). On the other hand, master curve technique is also an important tool for the analysis of drying characteristic. It helps to develop a relationship between the dependent and independent variables by including more number of independent factors (Bezbaruah and Hazarika, 2014). As a result, of which prediction capability of the model increases in terms of greater correlation coefficient.

Besides that artificial neural network integrated particle swarm optimization (ANN-PSO) is a new technique for the modeling and optimization between the independent and dependent variables. Very few researchers have used this technique. In this technique weight bias value obtained from the best ANN architecture is utilized as the input of the particle swarm optimization. Particle swarm optimization is based on the imitation of the preying behavior of birds or fishes (Kennedy and Eberhart, 1995). In PSO, bird is assumed as possible solution in the searching space. The optimization is done by putting a fitness function for all the birds known as particles. In the study, this approach has been used for developing an optimum relationship between critical drying temperatures vs time, moisture content and drying temperature. The objectives of this study were to find out thin layer drying kinetics of paddy under low temperature conditions by using mathematical modeling, master curve technique and ANN modeling and to develop a relationship between the critical drying temperature vs time, moisture content and drying temperature of paddy for the evaluation of taste.

2 Theoretical considerations

Modeling of the drying process is necessary, in order to describe the single layer drying behavior of paddy and to predict it under different drying conditions. It has been established that liquid and/or vapor diffusion is mainly responsible for the drying phenomenon of biological product during falling rate period. There are mainly three categories of thin layer drying models namely theoretical, semi-theoretical and empirical, which generally describe the drying phenomenon of these materials. The semi-theoretical models are in the form of Fick's second law which are generally obtained from the general series solution of Fick's second law or modification of simplified models. Equation 1 represents the Fick's second law (Panchariya et al., 2002).

$$\frac{\partial(MC)}{\partial t} = D_{eff}\frac{\partial(MC)^2}{\partial r^2} \quad (1)$$

The initial and boundary conditions may be expressed as follows:

At t=0, MC=MC_i , for 0<r<R

At t>0, MC=MC_e, for r = R (top, evaporating surface)

At t > 0, $\frac{\partial(MC)}{\partial r} = 0$, for r = 0 (bottom, non-evaporating surface)

Several analytical solutions are there in order to solve the Fick's second law. Equation 2 shows the general series solution of Fick's second law for paddy.

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

By considering n=1 (for longer drying time), Equation 2 can be simplified as follows:

$$\ln(\mathrm{MR}) = \ln\left(\frac{8}{\pi^2}\right) - \left(\frac{\pi^2 D_{eff}}{4L^2}\right)t \quad (3)$$

The gradient form of the linear regression of the "ln (MR) vs t" is taken into consideration for calculating the effective diffusivity. L (m) is half thickness of the paddy grain (Panchariya et al., 2002).

Different thin layer drying models (based on Equation 1) used for the paddy drying are shown in Table 1.

Table 1 Thin layer drying curve model

Model name	Type	References
Newton	MR=exp(-kt)	Mujumdar (1987), Diamante and Munro (1993), Midilli et. al. (2002), Zhang and Litchfleld (1991) and Wang and Singh (1978)
Page	$\mathrm{MR} = \exp(-\mathrm{k}t^n)$	
Midilli model	$\mathrm{MR} = \mathrm{a}\exp(-\mathrm{k}t^n) + +\mathrm{bt}$	
Henderson and pabis	MR=aexp(-kt)	
Two term model	MR=a*exp(-k*x)+(1-a)*exp(-k*a*x)	
Wang and Singh	MR=1+b*x+a*x^2	

Arrhenius type Equation (Lopez et al., 2000; Akpinar et al., 2003), as shown in Equation 4, is mainly used for calculating the activation energy.

$$\mathrm{D} = D_0\exp\left(-\frac{E_a}{RT_a}\right) \quad (4)$$

Here, E_a is the energy of activation (kJ/mol), R is universal gas constant (8.3143 kJ/mol K), Ta is absolute air temperature (K), and D_0 is the pre-exponential factor of the Arrhenius equation (m^2/s). By plotting between the ln (D) and $\frac{1}{T_a}$, we get a slope from which we can easily determine the activation energy.

2.1 Generalized drying model

For generalization of the best fitted model to individual sets of drying data, it needs to be extended over a range of operating conditions. Generally two approaches detailed below were considered.

2.1.1 Generalization of drying constant

For BM, the dependence of the drying rate constant, k on drying temperature and slice thickness variables was then described in the Arrhenius type model (Equation 5) derived using regression analysis:

$$k = k_0 \exp\left(\frac{E}{T}\right) \quad (5)$$

Where K_0 = Pre exponential factor of Arhenius equation, E is activation energy, T is absolute air temperature (K).

2.1.2 Technique of master curve

Superimposition of MR (t) plots followed by the shifting towards central position is done in order to produce master curve. In first instance of shifting, MR (t) of three different drying temperatures at a given dimension is shifted to a reference temperature for obtaining the dimensionless average temperature shift factor of a_T following an equation similar to Equation 6 (Bezbaruah and Hazarika, 2014).

$$log a_{h,i} = \log t_R - \log t_i \quad (6)$$

2.2 Artificial neural network modeling

An artificial neuron is a computational model which is based on the natural neurons. Due to interactions through large number of simulated neurons information processing occur in a neural network. Four important components are there in this simulated neuron, or unit:

1. Input connections (synapses), through which the unit receives activation from other units.
2. Summation function that forms a single activation by combining the various input activations.
3. Threshold function that converts this summation of input activation into output activation.
4. The output connections (axonal paths) by which a unit's output activation arrives as input activation at other units in the system.

One type of network sees the nodes as 'artificial neurons'. These are called artificial neural networks (ANNs). Many processing elements connected by links of variable weights develop artificial neural-networks (ANNs) which are massive parallel systems. Among many ANN paradigms back propagation network is the most popular one. Each layer is connected to the proceeding layer by inter connection strengths or weights W which finally constructs the network consists of layers of neurons. Figure 1 illustrates a three-layer neural network consisting of input layer (L_I), hidden layer (L_H) and the output layer (L_O) with the inter-connection weights Wih and Who between layers of neurons. Appropriate weight adjustments necessary to minimize the errors are evaluated by back propagation which is done by comparing predicted outputs to known outputs followed by correction of initial estimated weight values (i.e., W_{ih} and W_{ho}) during a training process. In modeling any process, the input neurons in the input layer (L_I) and output layer (L_H) consist of the input and output of the process, respectively. However, in the subsequent section for generalization, the output of hidden neurons in the hidden layer is denoted by H_{oj} for j^{th} neuron and output of the output neuron in the output layer L_O is denoted by O_j for j^{th} neuron. L, M and N are the number of neurons in input, hidden and output layers, respectively.

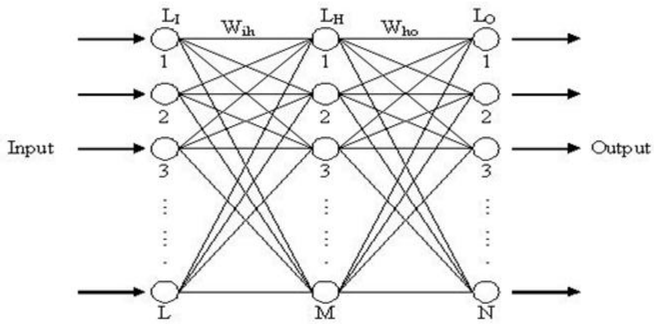

Figure 1 Configuration of three layer neural network.

The total input (H_{ij}) to hidden units j is a linear function of outputs (x_i) of the units that are connected to j and of the weights w_{ij} on these connections i.e.

$$H_{ij} = \sum_i x_i w_{ij} \quad (7)$$

A hidden unit is a non-linear function of its total input which has a real-value output (H_{oj}). Biases (θ_j) are introduced as an extra input to each unit which always has a value of one.

$$H_{oj} = \frac{1}{1+e^{-(H_{ij}+\theta_j)}} \quad (8)$$

The activation functions namely tangent sigmoid functions (Equation 9) were used for the ANN modeling. These two functions were used in the hidden layer and output layer respectively. The mathematical equations for these functions are shown below:

$$f_{act}(x) = \frac{1}{1+\exp(x)} \quad (9)$$

2.3 Particle swarm optimization

Particle swarm optimization was based on the imitation of the preying behavior of birds or fishes (Kennedy and Eberhart, 1995). In PSO, bird is assumed as possible solution in the searching space. The optimization was carried out by putting a fitness function for all the birds known as particles.

In the D-dimensional search space swarm can be indicated by ith particle, which is specified by a D-dimensional vector s=(S1, S2…..SD), whereas the velocity of the particle is represented by V= (V1, V2, ...VD). On the basis of best position of the previously visited ith particle, Pbest vector was decided. Best particle in the swarm is denoted by g index and the iteration number is denoted by superscripts. Manipulation of the swarm was done by using following Equations of 10 and 11:

$$V_i^{k+1} = W^k V_i^k + C_1 R_1^k (P_i^k - S_i^k) + C_2 R_2^k (P_g^k - S_g^k) \quad (10)$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \quad (11)$$

Where, W is the inertia weight; C_1 and C_2 are positive constants, i.e., cognitive and social parameters respectively; R_1 and R_2 are uniformly distributed random numbers in the range [0-1]; i = 1, 2, ...N and N is the size of the swarm, and k = 1, 2, ... is the current iteration (Hanafi et al., 2015). For solving the optimization problem, general code developed in MATLAB R2012a was used. The flowchart of the PSO algorithm is shown in Figure 2.

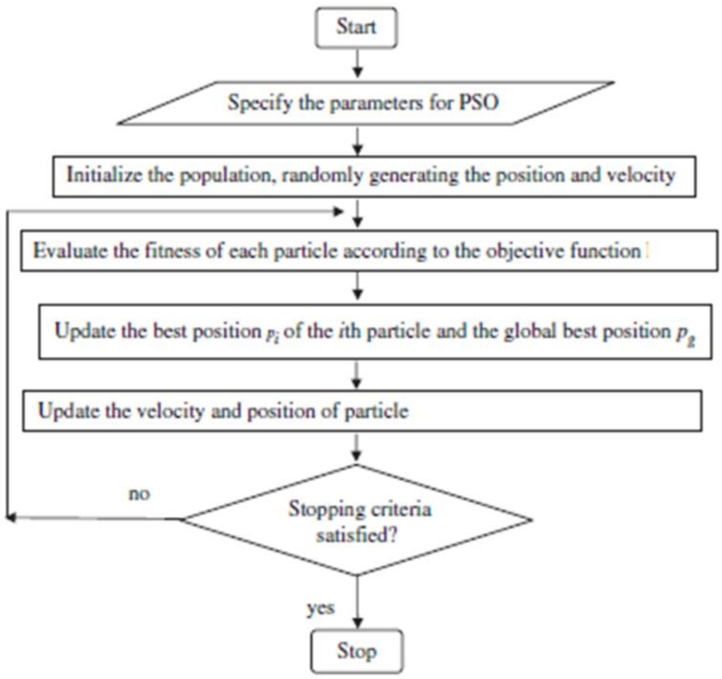

Figure 2 Flowchart of PSO algorithm (Liu et. al., 2008)

3 Methods and materials

3.1 Paddy sample

For the drying experiment, Aijung paddy (Oryza sativa Linn) available in Assam was collected from the local market of Tezpur University.

3.2 Paddy moisture content determination

Moisture measurement method for ungrounded grain and seeds (ASAE, 1988) was used for determining the moisture content of the paddy. Digital balance was used for measuring the sample weigh and finally to analyze the moisture content.

3.3 Drying chamber

The drying chamber is schematically shown in Figure 3. The chamber is of 21 cm diameter and 25 cm length. There is a flange in the upside in order to tight the chamber. The control panel consists of Main Switch Air velocity-(0%-98%), Process timer blower switch (green button-ON and red button-OFF) and heater (0 ℃-100 ℃). Low temperature and low velocity drying condition were provided by controlling the heater and air blower. The paddy was kept in the chamber up to a depth of 2 cm for the thin layer drying of paddy at low ambient temperature.

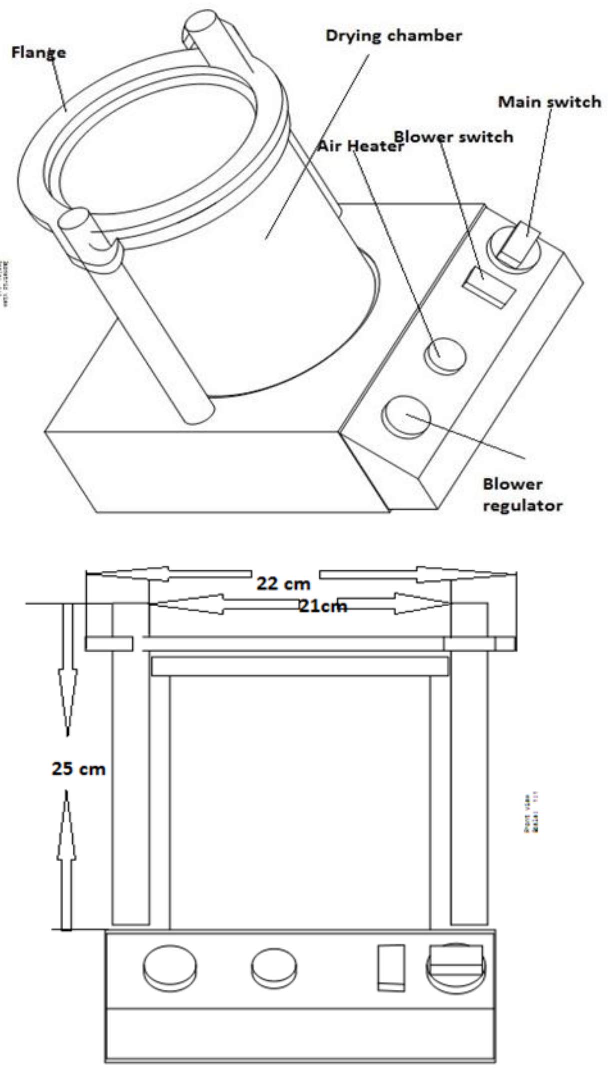

Figure 3 Schematic diagram of drying chamber and its dimensions

3.4 Experimental procedure

For the drying experiment paddy with initial moisture content 20% wb was prepared. Drying was carried out under the low ambient temperatures ranging from 20 ℃-40 ℃ with a constant air velocity of 1.41 m/s. Before starting the experiment, paddy samples were kept at room temperature in order to reach the temperature of the laboratory. After that drying experiments were performed in a batch dryer at specified air temperature until the moisture content reduced to less than 13% wb. For each experiment, drying time was estimated accurately after conducting a number of drying runs. The paddy samples were collected from the drying chamber at specified time steps of 5, 10, 15, 20 minutes (and so on) for determining the moisture content with the help of electronic balance until the finish of the drying run.

3.5 Moisture ratio

For normalizing the drying curves, the moisture content data of paddy during the thin layer drying experiments had been converted to a dimensionless parameter called Moisture Ratio (MR).

$$MR = \frac{M - M_e}{M_0 - M_e} \qquad (12)$$

Where M=moisture content at time t.

M_0=Initial Moisture Content.

M_e=Equilibrium Moisture Content.

4 Results and discussions

4.1 Drying curves

The effect of temperature on the drying of harvested paddy variety Aijung has been shown in Figure 4. As the temperature increases, drying rate increases and consequently moisture ratio decreases first. At the initial stage of drying, moisture removal is faster due to the diffusion of surface moisture and gradually it decreases. As a result, gradual leveling of the drying curve is observed.

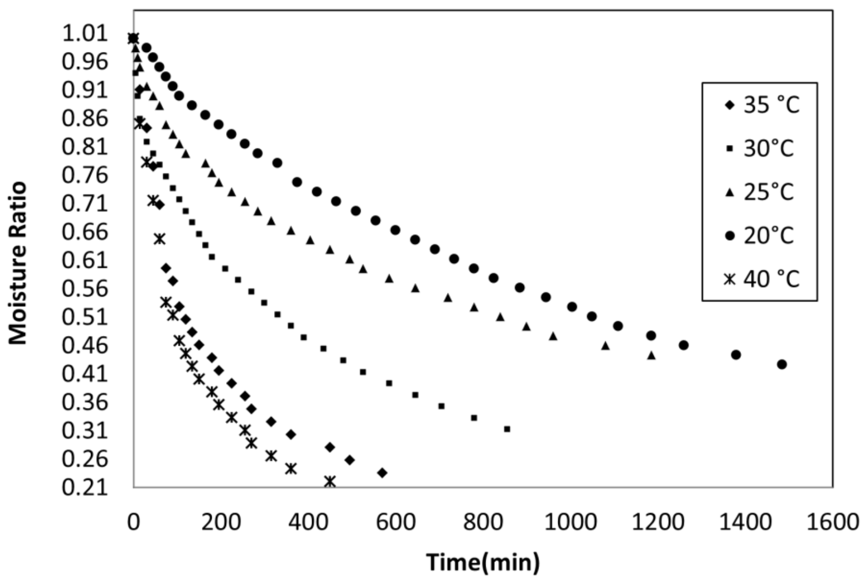

Figure 4 Variation of Moisture ratio of paddy (Initial moisture content-20%) with time

4.2 Selection of best mathematical model

For analyzing drying behavior of paddy, the thin layer drying equations listed in Table 1 were used. The best model was selected on the basis of correlation coefficient (R^2), Sum of square error (SSE) and Root mean square error (RMSE) in order to account for the variation in the drying curves of dried paddy. Table 2 shows the statistical results of the selected models fitted for the dried paddy having initial moisture content of 20%.

Table 2 Statistical results obtained from the selected models

Model			**Drying temperature**				
			20℃	25℃	30℃	35℃	40℃
Newton	Statistic of fit	R^2	0.9591	0.8227	0.8310	0.8222	0.8773
		RMSE	0.0490	0.0710	0.0734	0.0828	0.0077
		SSE	0.2577	0.3891	0.3183	0.2610	0.108
Page	Statistic of fit	R^2	0.9853	0.9951	0.9976	0.9804	0.9839
		RMSE	0.0295	0.0119	0.0088	0.0278	0.0288
		SSE	0.0918	0.0108	0.0044	0.0287	0.0141
Midilli model	**Statistic of fit**	$\mathbf{R^2}$	**0.9982**	**0.9984**	**0.9978**	**0.9883**	**0.9932**
		RMSE	**0.0069**	**0.0060**	**0.0083**	**0.0212**	**0.0199**
		SSE	**0.0046**	**0.0037**	**0.0039**	**0.0158**	**0.0059**
Henderson and pabis	Statistic of fit	R^2	0.9694	0.9217	0.9256	0.9201	0.9847
		RMSE	0.0426	0.0475	0.0491	0.0562	0.0290
		SSE	0.1913	0.1718	0.1402	0.1172	0.0134
Two term exponential	Statistic of fit	R^2	0.9931	0.8856	0.9043	0.8964	0.9477
		RMSE	0.0202	0.0574	0.0557	0.0303	0.0520
		SSE	0.0429	0.2511	0.1803	0.0312	0.0460
Wang and singh	Statistic of fit	R^2	0.9704	0.9659	0.9574	0.8254	0.8856
		RMSE	0.0417	0.0311	0.0372	0.0393	0.0769
		SSE	0.1847	0.0749	0.0803	0.0525	0.1008

From the results shown in Table 2, Midilli model is selected as the best model for predicting the drying behavior of this type of paddy with the highest value of R^2, lowest value of SSE and RMSE than the other models. The model constants of the Midilli model for the paddy having initial moisture content of 20% are illustrated in Table 3.

Table 3 Values of the drying constant and coefficients of the best model (*Midilli model)*

Temperature	20%imc			
	a	**b**	**k**	**n**
20	1.010	1.22E-005	0.00247	0.8143
25	1.009	3.30E-005	0.16896	0.6153
30	0.986	-3.65E-006	0.24241	0.5952
35	1.070	0.00021	0.49802	0.5130
40	1.008	0.00033	0.5876	0.7853

4.3 Generalization of drying model parameters and global drying rate constant

From Table 3 we can observe that the drying rate constant k increases with the increase in drying temperature. This is due to the fact that the driving force for heat and mass transfer is enhanced by higher temperature. The other drying constant n showed a decreasing trend. But it was unable to describe the drying behavior of the paddy. However, other constants like a and b did not show any kind of trend. Hence, the correlation between the drying rate constant and Arrhenius equation is given by the Equation 13.

$$k=2890.72 \exp(-2727.31/T_{abs}) \quad (13)$$

By inserting function *k* (Equation 13) into the 4-term variables Midilli model, it allows the moisture ratio's expression to be reduced to a 2-term variable model known as the single model which is expressed as a function of drying time and drying temperature (Equation 14), with the constant *a* = 1.08603, *n* = 0.526139 and *b* = 0.006293 fitted using data obtained from entire experimental data.

$$MR(t,T)=1.08603\exp(-kt^{0.526139})+(0.006293)t \quad (14)$$

$$R^2 = 0.9776$$

4.4 Generalization based on shift factor using master curve technique

By taking 30℃ as reference drying temperature, master curve was obtained corresponding to the temperature reduced time of t'=t.a_T. The values of the temperature shifting factor (a_T) are listed in Table 4. The relationship between a_T and temperature T (℃) was found as given in Equation 15.

$$a_T=5\text{X}10^{-07}\times T^{4.317} \quad (15)$$

$$R^2 = 0.986$$

Table 4 Value of temperature shifting factor at different temperatures

Temperature, ℃	**Temperature shifting factor, a_T**
25	0.524
30	1
35	2.258

For deriving relationship between moisture ratio, drying time and drying temperature, the final master curve was fitted with Midilli model (R^2=0.998)

$$MR(t', T)=1.01313\exp(-0.212828 (t')^n + 0.000927691 t' \quad (16)$$

$$t' = t.\ a_T = t.5E\text{-}07 \times T^{4.317}$$

From Equations 15 and 16, it can be observed that master curve fitted with Midilli model by using superposition technique gave best fit with a R^2 value of 0.998 than the global drying constant model.

The master curve obtained due to temperature shifting factor is shown in Figure 5 which is a function of moisture ratio and time (t. a_T). In this figure, moisture ratio predicted by generalized k and master curve technique are compared with the experimental values of moisture ratio. It was observed that the performance of master curve was better in compared to globalize drying rate constant (k) method.

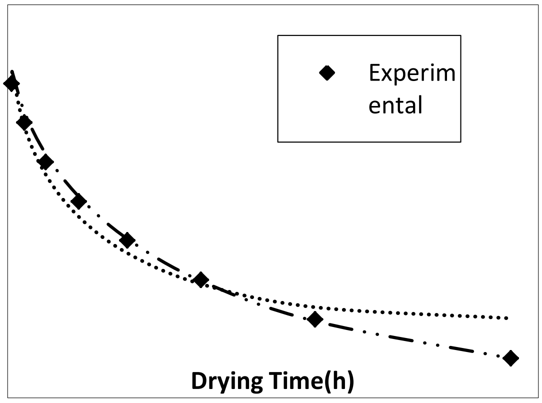

Figure 5 Master curves for paddy drying fitted to Midilli-Kucuk model obtained after temperature-thickness superposition, and comparison with plot obtained from generalized drying rate constant (*k*)

4.5 ANN Modeling for the moisture sorption isotherm of the rough rice

4.5.1 Selection of ANN architecture

For obtaining stronger correlation between the independent and dependent variables of the drying process, ANN modeling was carried out. It was done in MATLAB-R2012a software by using neural network toolbox. Levenberg-marquardt back-propagation algorithm was used for developing the ANN model. Depending on independent and dependent variables, the number of neuron in the input and output layer was decided. The number of neuron in the input and output layer was decided on the basis of two independent variables (drying temperature and time) and one dependent variable (Moisture ratio) respectively. The numbers of neuron in the hidden layer was decided by trial and error approach. The experimental data were divided into three portions for the purpose of training, testing and validation (75% for training, 15% for testing and 15% for validation). For each architecture, 10 runs were carried out. Based on the average mean square error (MSE), optimum architecture (2-55-1) was selected. The decreasing trend of average MSE obtained from each architecture is shown in Figure 6. From the figure, it can be observed that average mean square error (MSE) for the best ANN architecture (2-55-1) is lowest.

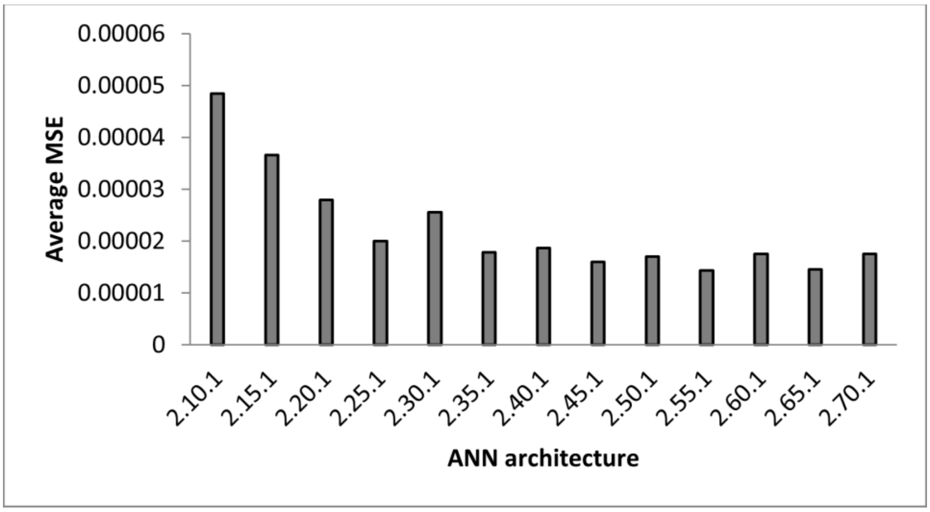

Figure 6 Selection of best ANN architecture on the basis of average MSE

From Table 5, performance of ANN architecture can be obtained. It shows superiority of ANN modeling over other modeling techniques in terms of highest R^2 and lowest MSE value. Comparison of the coefficient of determination (R^2) among the three modelling techniques is shown in Figure 7. From the figure, it can be concluded that 2-55-1 is the best model for describing thin layer drying behaviour of paddy under low temperature conditions.

Table 5 Result of best ANN architecture for different drying temperature

Drying Temperature, ℃	R^2	MSE
20	0.9999	6.29E-06
25	0.9998	2.52E-05
30	0.9999	1.60E-07
35	0.9999	3.26E-12
40	0.9999	2.26E-07

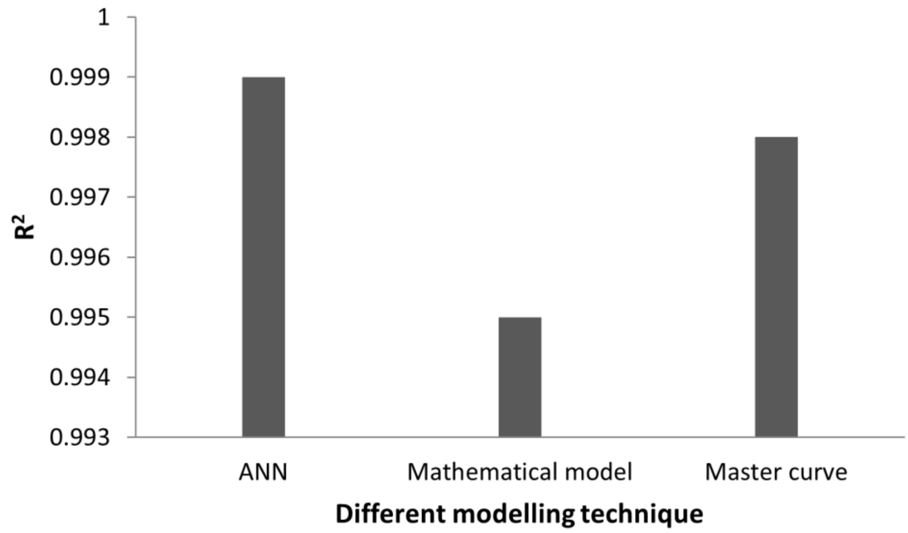

Figure 7 Comparison between the three modeling techniques in terms of R^2

4.6 Modeling of the critical drying temperature by using PSO integrated ANN approach

Critical drying temperature is an important factor for the paddy drying which guarantees the taste of the paddy. On the basis of critical temperature, it can be assured that taste of paddy is no more than 5% after reaching the final moisture content. The relationship between the critical drying temperature and moisture content can be shown by the following Equation of 17:

$$T=\exp(5.021-0.058M) \quad (17)$$

Where, T is critical drying temperature (℃) and M is the initial moisture content of the paddy (%, wb.).

In case of paddy dryer, this equation can be utilized for determining the critical drying temperature in order to preserve the taste (Zheng et al., 2007). In this study, changes in moisture content with respective to time at a particular drying temperature was utilized for determining the critical drying temperature at each time interval. It was continued up to the final moisture content. The calculation was done at five drying temperatures (20℃, 25℃, 30℃, 35℃ and 40℃).

For making a relationship between depended variables namely critical drying temperature and independent variables namely drying temperature and time, artificial neural network (ANN) modeling was used. For the ANN modeling, selected architecture was 2-55-1. The modeling was carried out by using feed forward ANN network. Optimization of network architecture on the basis of minimization of error was the main objective of ANN modeling. By using random number generation, the values of '*u*', '*w*', '*Th'* and '*To'* were obtained (Khwas et al., 2015). For the analysis total number of input and output data were 300. For the simulation of the network total numbers of cycles were 1000. The values obtained for '*u*', '*w*', '*Th'* and '*To'* are given below:

$$u = \begin{pmatrix} 0.0095 & 0.0190 & 3.6337 \\ 0.0002 & 0.0003 & 0.1901 \\ 0.0313 & 0.2132 & 3.3648 \end{pmatrix}$$

$$w = (-6.0259 \quad -5.9745 \quad -7.4482)$$

$$Th = \begin{pmatrix} 4.8082 \\ 0.3425 \\ -4.3173 \end{pmatrix}$$

$$To=(0.45221)$$

These values were utilized for obtaining the relationship between independent and dependent variables. For this study, in order to develop the relationship in terms of y=f (x1, x2, x3), *tansig* was used. This equation was used as objective function in case of particle swarm optimization (PSO). For the particle swarm optimization the constraints were as follows:

Constraints:
Drying temperature range: 20<x1<40
Time range: 0<x2<1500
Moisture content (% wb): 13<x3<20

By using the values of '*u*', '*w*', '*Th'* and '*To'* from the ANN modeling, input for the particle swarm optimization was provided. In PSO algorithm, the parameters were set as follows. The initial population size was 40 particles. The values of acceleration constants, c1 and c2, were both 0.5. The inertia weight w decreased linearly from 0.5 to 0.1 with the increase of generations. The maximum number of generations was set to 500 PSO. After the optimization process it was predicted that for getting optimum critical drying temperature, the temperature should be 34.7℃, time should be 1297 minutes and the moisture content should be up to 10% wb. So, for further studies related to critical drying temperature and moisture content of paddy during drying, these data can be used. Finally, the taste of the paddy during drying, can be controlled by predicting required critical drying temperature based on optimum operating conditions.

4.7 Comparison of thin layer drying behavior of different varieties of paddy on the basis of PAGE model

For checking the effect of paddy variety and equilibrium moisture content on the drying kinetics, the drying behavior of paddy variety (Wells) as mentioned by Ondier et al. (2010), was compared with the present variety (Aijung) on the basis of page model. The values of the drying constants k and n for drying of both the paddy varieties under specific drying temperature are shown in Table 6. It was observed that the drying curve of both the paddy varieties follows similar type of trend.

Table 6 Drying parameters of the Page model for the paddy varieties

Paddy type	k	n	EMC,%DB	IMC,%DB
Wells	0.2656	0.64936	10.7901	24.37
Aijung	0.2518	0.6662	10.5	25

If paddy moisture content is calculated in dry basis (% db) on the basis of k and n values obtained for Aijung variety, we observe that percentage error become very less 0.50%. The plot of moisture content and time of drying for both paddy varieties is illustrated in Figure 8.

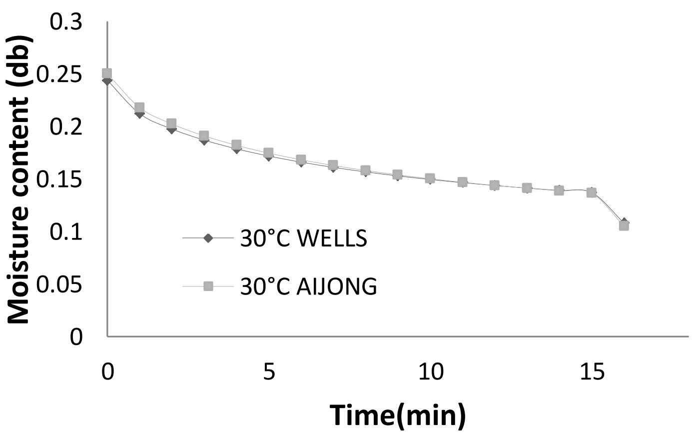

Figure 8 Thin layer drying behavior of paddy varieties- Wells and Aijung under 30 ℃.

4.8 Effective diffusivity

Effective diffusivity was obtained from the slope of the graph between ln (MR) and time by using the average diameter of the paddy. Figure 9 represents the dependence of effective diffusivity on drying temperature. Here, we observed that as the temperature increased, diffusivity also increased. The reason is that, when the temperature increases, amount of energy available for diffusion also increases. As a result molecules move at a faster rate and diffusivity increases.

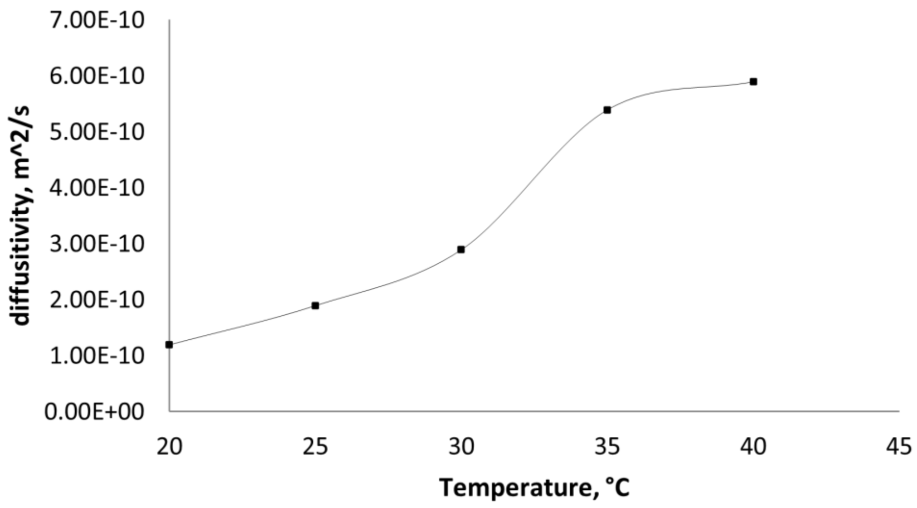

Figure 9 Effective diffusivity variations with drying temperature

4.9 Activation energy

Activation energy was calculated from the Arrhenius type Equation (Equation 4). Activation energy of this type of paddy was 54.23 kJ/mol.

5 Conclusions

The impacts of low ambient temperature (20℃-40 ℃) on the thin layer drying behavior of Aijung paddy were studied. It was observed that Midilli model fitted the best in order to describe the drying behavior of this type of paddy. At low ambient temperature (20 ℃-40 ℃), drying constant for the drying of paddy showed an increasing trend with the increase of drying temperature. This is due to the fact that the driving force for heat and mass transfer is enhanced by higher temperature. Midilli model was generalized by using two approaches (i) globalization of drying rate constant and (ii) the technique of master curve obtained by superposition of temperature. Master curve technique gave best fit with a R^2 value of 0.998 than the global drying constant model. ANN modeling was also used to find out proper drying kinetics of paddy. Best architecture for the ANN modeling was 2-55-1, which showed the best performance than the other modeling techniques. Modeling of critical drying temperature was also carried out as it is important for taste evaluation of paddy during drying. By using ANN-PSO (artificial neural network-particle swarm optimization) approach, a relationship between the dependent variable i.e critical drying temperature and independent variables namely drying temperature, time and moisture content (% wb) was developed. Effective diffusivity linearly increased with increase of temperature. The value of activation energy of this type of paddy was 54.23 kJ/mol.

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