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ANN Modelling for Prediction of Moisture Content and Drying Characteristics of Paddy in Fluidized Bed

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Abstract— **Drying characteristics of paddy were studied in inclined bubbling fluidized bed dryer at the air temperatures of 55, 60 and 65°C, air velocities of 1.1, 1.6, and 2.1 m/s, dryer inclination angles of 0˚, 15˚ and 30˚ and inventories of 0.5 to 2.5 kg. By applying the artificial neural networks (ANNs), moisture content of paddy was predicted under the various input conditions of different drying air temperatures, superficial air velocities, inclination angles of dryer, inventories and drying time. The learning of ANN is accomplished by feed forward back propagation algorithm. The simulated results are compared with the experimental results. The effect of input parameters is significant on the moisture content and drying time. The optimized ANN was found 12 neurons in hidden layer. The 1st and 2nd functions are tansig and logsig, respectively at 84 iterations and error goal is 0.00006. The ANN model gives the average absolute relative error (AARE) of an acceptable level of 3.3% with a correction coefficient (Rcc) of 99.6% and it is found that moisture content predicted by the neural network model developed in this work is in a good agreement, which have a non-linear relationship with each other is believed to be an accurate prediction the moisture content of grain.**

Index Terms— **Inclined fluidized bed, forward back propagation neural network, moisture content, paddy**

I. INTRODUCTION

Rice is the staple food for more than half of the world's population. About 90% of the world's rice is produced and consumed in Asia. The rice quality and energy used in drying were significantly dependent on the method of drying. Drying of agricultural materials is a complex and non-linear process with long time delay. Therefore, it is very difficult to establish a precise mathematical model for grain drying control. Artificial neural network (ANN) is a nonlinear modeling that is generally used to model complex relationships between inputs and output parameters. A more realistic and accurate predictions can be obtained through ANN analysis and it was successfully used to describe the drying characteristics of agricultural crops and to estimate moisture ratio.

Gupta et al., (2016) used ANN for estimation of crop variables and reported that the estimated values by ANN were very close to the observed values of the crop variables. Ngunzi et al., (2014) studied mathematical models of deep bed grain drying to control moisture content and temperature in a grain drying chamber and reported that there is a strong correlation between moisture content and drying time for both simulated and experimental data. They also mentioned that the developed simulation model can be used to predict drying in the automated grain dryer. Dahikar and Rode (2014) studied the agricultural crop yield prediction using feed forward back propagation artificial neural network and reported that ANN is beneficial tool for prediction of crop yields at rural district. Bejo et al., (2014) presented a review on the use of ANN in predicting crop yield using various crop performance factors. They reported that ANN provides better interpretation of crop variability compared to the other methods. Studies on drying of various products like green pea, corn, Jujube fruit, peach, paneer, wheat etc were also reported by Momenzadeh et al., (2012), Cao et al., (2007), Motevali et al., (2012), Yazdani et al., (2013), Srivastav and Kumbhar (2014) and Kashaninejad et al., (2009), respectively using ANN for modeling and prediction of various drying parameters.

Golpour et al., (2015) predicted the moisture content of paddy in thin layer drying using machine vision and artificial neural networks. They reported that ANN was a proper method for predicting moisture content of paddy. Zare et at., (2015) applied ANN and predicted the drying time, variations in paddy moisture content and quality attributes of paddy in combined hot-air/infrared drying. They presented that ANN modeling can effectively contribute to the prediction of the mentioned parameters. Sarker et al., (2015) investigated the energy and exergy analysis of industrial fluidized bed paddy drying and reported that exergy can be increased through providing sufficient insulation on dryer body and recycling the exhaust air. Sarker et al., (2015) developed a mathematical model in determining suitable operating parameters for industrial scale fluidized bed dryer during drying of high impurity moist paddy and reported that it is capable of predicting outlet paddy moisture content and air temperature well.

Lilhare and Bawane (2014) designed a neural network based automated controller for paddy drying and it managed the steam temperature and blower motor speed to achieve constant paddy drying time. They observed that the developed ANN controller can be used to control the paddy drying process and it helped in controlling the drying time at almost constant value which improved the quality of rice. Zare et al., (2012) investigated ANN for predicting the moisture content during drying of paddy. They reported that ANN with 8 neurons in first and 14 neurons in second hidden layers and Tansig transfer function with trainlm back propagation algorithm is the most appropriate configuration for prediction of paddy moisture variation in thin layer form in infrared-hot-air dryer. Tohidi et al., (2012) studied the performance indices of deep bed drying of rough rice using artificial neural networks and compared the ANN approach to the multivariate regression method, and determined the sensitivity of the ANN model to the input variables. They reported that the values of all of the drying indices predicted by the ANN were closer to the experimental data than linear

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and logarithmic regression models. They also mentioned that the output variables were significantly affected by the dependent variables, however, air temperature and air relative humidity showed the maximum and the minimum influence on the network outputs, respectively. Bizmark et al., (2010) predicted the paddy moisture content in a continuous plug flow fluidized bed dryer at different scales and operating conditions.

Jittanit et al., (2010) investigated the energy consumption of paddy drying in a large-scale milling plant and some drying experiments were conducted in a laboratory. They concluded that the energy cost of the plant could be reduced if an in-store dryer was used after the first-stage drying. Kumara et al., (2009) investigated the complex flow rate of paddy rice grains through the orifices on the circumference of the horizontal rotating cylindrical drum of a hand tractor drawn or self-propelled drum seeder using regression analysis and ANN. They reported that neural network is better to predict the flow rate than regression equation with overall mean absolute percentage relative error of 4.85%. Atthajariyakul and Leephakpreeda (2005) studied fluidized bed paddy drying for determination of optimal conditions in order to guarantee good quality and consume energy efficiently. Tirawanichakul et al., (2004) studied the simulation of grain quality for in-store drying of paddy and reported that the degree of whiteness depends on temperature, relative humidity, loading capacity and airflow rate. Experimental and modelling of paddy drying in the inclined fluidized bed dryer for prediction of moisture content and drying characteristics using ANN method has not been reported.

II. MATERIALS AND METHODS

The bubbling fluidized bed dryer system consists of a centrifugal blower powered by a 15 HP electric motor, three electric heaters each of 1kW capacity and fitted inside the air blow pipe, orifice plate, distributor plate, dryer column, manometer, thermocouples, and data acquisition system. The desired bed inclination at an interval of 15° from the vertical is achieved using the inclination flange which is connected to the end of the air blow pipe. The dimensions of the dryer are 100 mm x 100 mm cross sectional area and 1625 mm column height. Twenty six pressure taps were used to measure the fluidized bed pressure drops on both sides of the column. The pressure drops were measured from the manometers using water as the manometer fluid. The manometer readings from each pressure tapings during the drying processes were recorded at an interval of 10 minutes from which the pressure drops were determined. The dryer column was fabricated using Plexiglas for visual observation. The paddy bed of batch sizes 0.5 to 2.5 kg were fluidized at three different dryer positions: vertical bed (0° inclined), 15° and 30° inclined beds with drying air temperatures of 55, 60 and 65°C and air velocities of 1.1, 1.6 and 2.1 ms^{-1}. At the start of the experiment, the blower was switched on and air mass flow rate and velocity were adjusted by means of gate valve installed in the air flow pipe. Air was heated and maintained constant at the required temperature by means of the heater coils. Drying air temperature was measured by the pre-calibrated K-type thermocouples and continuously recorded using the data acquisition system. Paddy of required inventory was loaded into the bubbling fluidized bed dryer. The pressure at different sections along the column of the dryer was recorded to obtain the pressure drop across the bed for fluidized bed behavior. Few grams of paddy samples were taken out at 10 minutes interval for the determination of the moisture content. The moisture content of the paddy was determined using a digital grain moisture meter having an accuracy of ±0.5%. The moisture meter was pre-calibrated using the standard oven method. The experiment was terminated when the moisture content in the paddy dropped to 12 % wet basis. Figs. 1(a) and (b) show the photographs of the fluidized bed dryer at 0° inclination and 15° inclination from the vertical.

III. ANN MODELING OF MC DATA

(a)

(b)

Fig. 1 Bubbling fluidized bed drier with the inclination of (a) $\theta = 0°$ and (b) $\theta = 15°$

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ANN model was applied to obtain a nonlinear relationship between input variables of air temperature, air velocity, dryer inclination angle, paddy bed inventory, and drying time and output variable of final moisture content. Modelling of MC data was based on the concept

$$MC = f(\theta, I, U, T, t) \ldots\ldots\ldots\ldots (1)$$

where MC is moisture content of paddy, θ is the inclination angle of the fluidized bed dryer, I is the inventory of paddy, U is the superficial velocity of air, T is the drying air temperature and t is the drying time. The ANN modelling was carried out by the multiple layer perception feed forward back propagation network. The most popular method practiced for supervised training of neural networks is the back-propagation training algorithm [Tsoukalas and Uhrig (1997), Hsiao et al., (2005)]. The typical architecture of which is illustrated in Fig. 2.

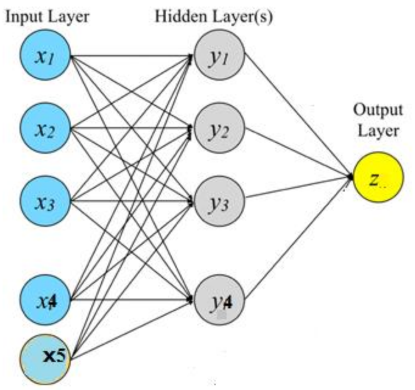


Fig. 2 Neural network architecture

The input layer of the neural network consists of 5 neurons representing the above mentioned parameters. The output layer consists of one neurons representing MC. Input data were divided into three parts for training, testing and validation, which were randomly selected. The ANN was trained with Levenberg-Marquardt (LM) learning algorithm. Training of the neural network was done by MATLAB software. ANN is a highly efficient method for solving non-linear optimization problems [Robi and Dixit (2003), Mujumdar et al., (2007)]. The input-output data sets ($MC = f(\theta, I, U, T, t)$) were used for training, testing and validation. The moisture content, inclination angle, inventory, superficial velocity, drying air temperature and drying time values were mapped to lie 0.1 and 0.9 before feeding the data into the network. The training of the neural network was carried out by varying the number of neurons in the hidden layer and adjusts its weights to minimize the error between the predicted and actual outputs. The predictability of the trained ANN model was verified via employing standard statistical parameters such as correction coefficient (R_{cc}), average absolute relative error (AARE) and average root mean square (RMS) error. They are expressed as:

$$R_{cc} = \frac{\sum_{i=1}^{N}(E_i - \bar{E})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N}(E_i - \bar{E})^2 \sum_{i=1}^{N}(P_i - \bar{P})^2}} \quad \ldots\ldots\ldots\ldots\ (2)$$

$$\text{AARE } (\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E_i - P_i}{E_i}\right| \times 100 \quad \ldots\ldots\ (3)$$

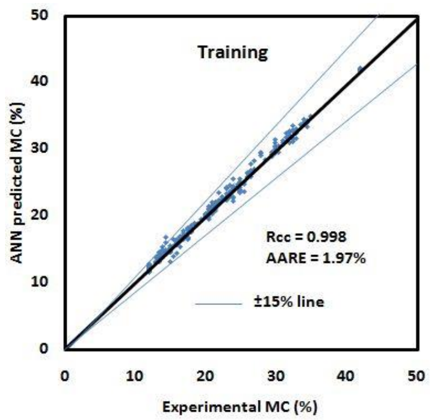
$$\text{RMS error} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_i - P_i)^2} \quad \ldots\ldots\ldots\ (4)$$

where E_i and P_i are the experimental and predicted value, respectively, and N is the total number of data used in the investigation. Once the ANN architecture was frozen based on training and testing process, the fitted neural network was validated with the input-output data sets, which were not used earlier for the training and testing purpose. The neural network was also used for simulation of MC under the experimental conditions. The present study is to develop and evaluate ANN model of the drying configuration and to predict the grain moisture content based on measures of error deviation from experimental data. In order to study the effect of different parameters on network performance, the model was run with changing parameters.

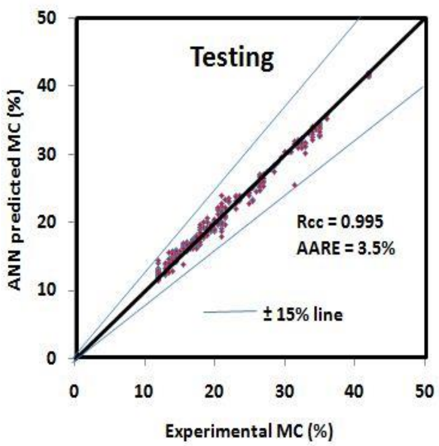
IV. RESULTS AND DISCUSSION

A. *Training, Testing and Validation of ANN Model*

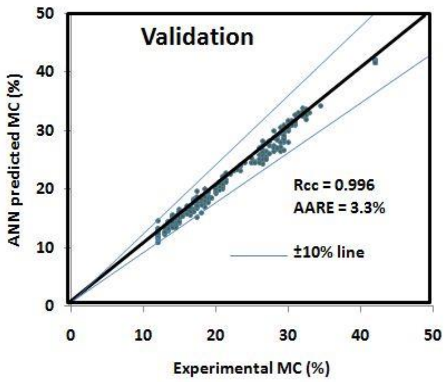
After a number of numerical experiments using the training and testing data sets, the best network architecture was achieved with 12 neurons in the hidden layer and transfer functions of tansig and logsig in hidden layer and output layer. The error goal of this optimized structure is 0.00006 and epoch is 84 iterations. Figs. 3(a) and (b) show the plots of neural network predicted vs. experimental value of MC during the training and testing, respectively. A diagonal line inclined at 45˚ from horizontal shown in both the figures indicates a perfect prediction. Fig. 3(a) reveals that most of the data points during training line are very close to this line indicating good prediction within a deviation error of ±15% during the training. The correction coefficient R_{cc} and average absolute relative error (AARE) for the training data set is 0.998 and 1.97%, respectively. As shown in Fig. 3(b), during the testing, most of data points could be predicted within a deviation error of ±15%. The R_{cc} value and AARE for the testing data set were determined as 0.995 and 3.5%, respectively. The final neural network model was validated independently using the data sets which were not used earlier for the purpose of training or testing. Fig. 3(c) shows the plot of neural network predicted vs. experimental value of MC could be predicted within a deviation error of ±10% during validation. The RMS error, R_{cc} and AARE for the validation data set are 0.19, 0.996 and 3.3%, respectively. The prediction establishes the confidence in the predictive capabilities of the neural network model.



(a)



(b)



(c)

Fig. 3 Correlation between experimental and predicted MC data after (a) training (b) testing and (c) Validation of ANN

B. Simulation of MC

Having gained confidence in the neural network architecture, MC was obtained by ANN simulation for the experimental conditions of inclination angle, inventory, velocity and temperature. In order to show the effects of various drying parameters on MC of paddy, the drying processes were continued at the different input conditions. Paddy moisture content variations with drying time are illustrated at different air velocities, air temperatures, inclination angles and inventories. Figs. 4, 6, 8 and 10 show the plot of the simulated MC at various conditions. Figs. 5, 7, 9 and 11 show the comparison of the ANN simulated and experimental MC for various conditions.

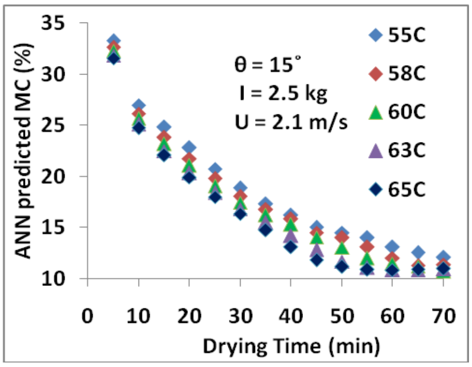


Fig. 4 Predicted MC at different temperatures

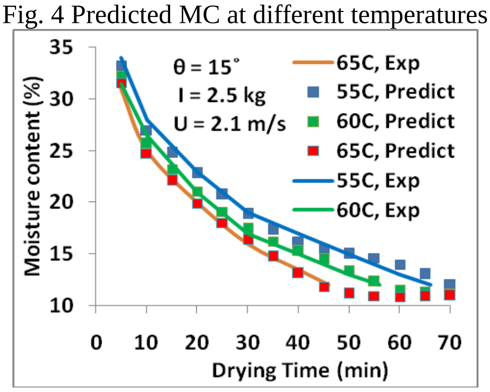


Fig. 5 Comparison between experimental and predicted MC at different temperatures

From the Fig. 4 it is observed that moisture content and drying time reduced when the air temperature was increased. The drying time decreased from 70 min to 45 min when the air temperature was increased from 55˚C to 65˚ and 35.7% of drying time decreased to get final MC. At the initial period of drying process, moisture content decreased significantly in the experiments. Also, as can be seen in Fig. 4 for air velocity of 2.1 ms-1, an inclination angle of 15˚, and an inventory of 2.5 kg, the lowest drying time was acquired at air temperature of 65°C to reach the final moisture content of 12% w.b. As shown in Fig. 5 the predictions are found to be very close to the experimental results of MC.

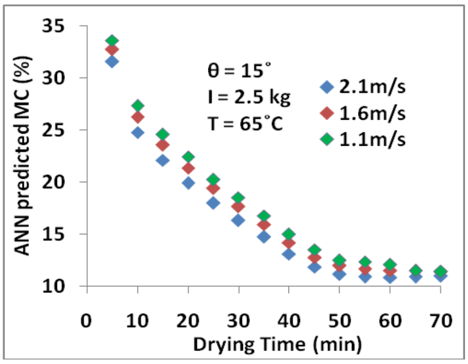


Fig. 6 Predicted MC at different velocities

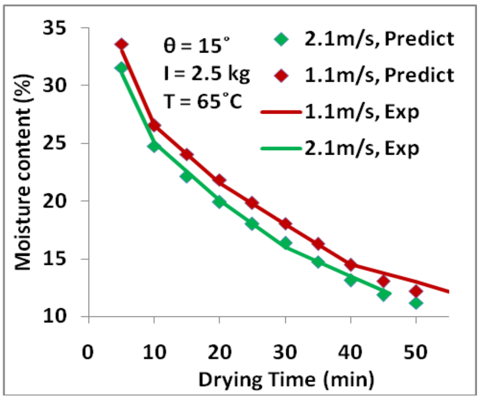


Fig. 7 Comparison between experimental and predicted MC at different air velocities

In the Fig. 6 it can be seen that MC and drying time decreased when the air velocity was increased. The drying times at air temperature of 65˚C and an inventory of 2.5kg are 67, 62 and 57 min, respectively for air velocity of 1.1, 1.6 and 2.6 m/s to drop the final MC of 12% (w.b). It is observed that drying time/kg paddy decreases by 15% when the air velocity is increased from 1.1 to 2.1 m/s. It can be seen that the predictions are found to be very close to the experimental results as shown in Fig. 7.

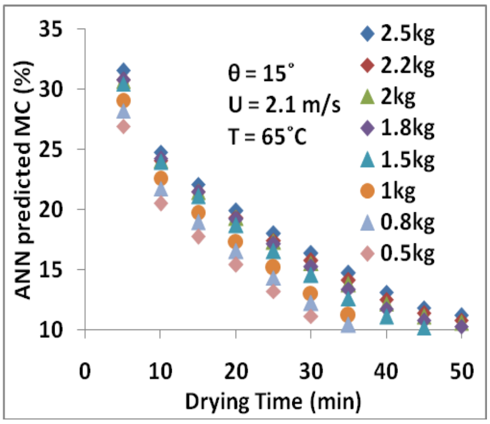


Fig. 8 Predicted MC at different inventories

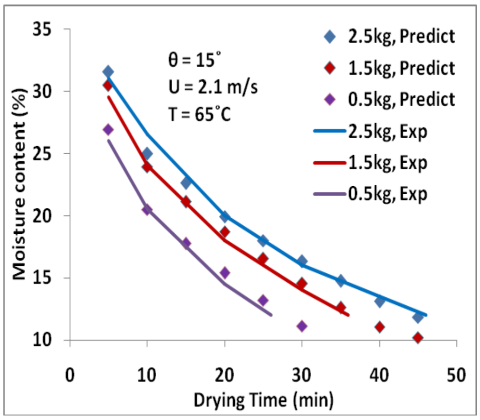


Fig. 9 Comparison between experimental and predicted MC at different inventories

The drying times at air velocity of 2.1m/s and air temperature of 65˚C are 25 and 41 min, respectively for the inventory 0.5 and 2.5kg to drop the final MC of 12% (w.b) as shown in Fig. 8. The corresponding drying times/kg paddy is 50 and 16.4 min. It is observed that drying time/kg paddy decreases by 67.2% when the inventory is increased from 0.5 to 2.5kg. As shown in Fig. 9. it is found that the predictions are approaching to the experimental results.

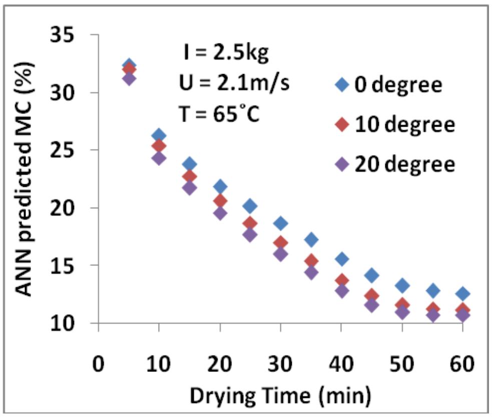


Fig. 10 Predicted MC at different inclination angles

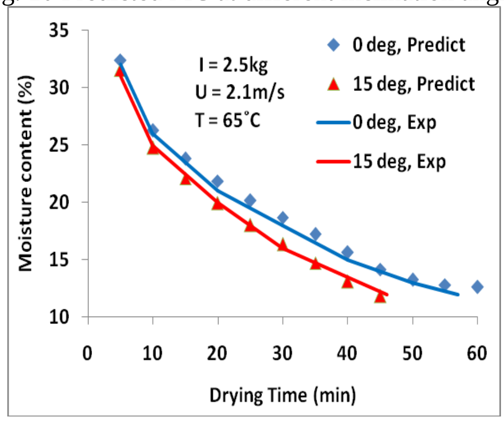


Fig. 11 Comparison between experimental and predicted MC at different inclinations

The drying times for the inventory of 2.5kg and air velocity of 2.1 m/s and air temperature of 65˚C are 60 min, 45 min and 40 min, respectively for $\theta = 0˚$, 10˚ and 20˚ to drop the final MC of 12% (w.b). Drying is found to be more efficient with $\theta = 10˚$ and 20˚ compared to $\theta = 0˚$. It is observed that drying time/kg paddy decreases by 33.3% when the inclination angle was increased from $\theta = 0˚$ to 20˚. According to Figs. 5, 7, 9, and 11 it is observed that the prediction and the experimental results are almost same. Hence ANN modeling can be used as a powerful tool for prediction of MC.

V. CONCLUSION

The drying behavior of paddy in BFB dryer and relationship of moisture content of paddy at the air temperatures of 55, 60, and 65°C and air velocities of 1.1, 1.6 and 2.1m/s, inclination angles of 0˚, 15˚ and 30˚, paddy bed inventories of 0.5 to 2.5 kg was investigated. The effect of various input parameters on MC and drying time was observed. When the input parameters were increased, MC and drying time/kg paddy were decreased. ANN is found to be a proper method for predicting moisture content of paddy. Best training performance to model moisture content was obtained with 12 neurons in the hidden layer and transfer functions of tansig and logsig in hidden layer and output layers. Results showed that the optimized network presented *Rcc* = 0.996 for prediction of moisture content of paddy and drying characteristics.

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