Experimental performance and artificial neural network modeling of solar drying of litchi in the parabolic greenhouse dryer

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Abstract

This paper presents experimental performance and artificial neural network modeling of drying of litchi flesh in a parabolic greenhouse solar dryer. The dryer consists of a parabolic roof structure covered with polycarbonate sheets on a concrete floor. This dryer has the base area of 5.5×8.2 m^2 and the height of 3.25 m. To investigate the experimental performance of the dryer for the drying of litchi flesh, 10 experiments were conducted. One hundred kilograms of litchi flesh were used for each experiment. The drying time of litchi flesh in the dryer was 3 days, whereas 5-6 days were required for natural sun drying under similar weather conditions. An artificial neural network (ANN) approach was used to model the performance of the dryer for the drying of litchi flesh. Using solar drying data of litchi flesh, the ANN model has been trained using the back-propagation algorithm. Seven sets of data were used for training and three sets were used for testing the ANN model. The performance of the dryer predicted by model was found to be very good.

Keywords:

Artificial neural network, parabolic greenhouse dryer, litchi, drying

1. Introduction

Litchi (Litchi Chinensis Sonn.) is one of the major fruits in Southeast Asia, grown mainly in northern Thailand and northern Vietnam. The mature litchi is almost spherical shape and has a dark red colour. The flesh of this fruit is consumed both as fresh and dried products. It is a seasonal fruit. The drying of this fruit during harvesting season ensures year round availability and preserves the taste of litchi. Furthermore, dried fruits are becoming popular as an alternative to fresh fruits because of the special flavor of the dried fruits which cause the demand for dried fruits to increase consistently in international markets.

A drying model for litchi is useful for optimum design and operation of the litchi dryer. For proper understanding of the transfer processes during drying for production of quality dried products and in order to conserve energy during litchi drying, it is essential to know its drying characteristics.

Considerable studies have been conducted to describe the drying of food and non-food materials [1-23]. Kaminski et al. [24] reported the application of an artificial neural network (ANN) to the modeling of drying kinetics and degradation kinetics and a theoretical foundation of the drying process description by means of ANN was presented. Several studies have been reported on ANN modeling of drying of food materials [25-35]. Trelea et al. [26] presented a methodology for building a fast nonlinear dynamic model of drying and wet-milling degradation using ANN, and the model was based on experimental data. Farkas et al. [27] applied ANN to an agricultural fixed bed dryer and concluded that the ANN could be effective for modeling of the grain-drying process. Bala et al. [29] reported on ANN modeling of the drying of jackfruit bulbs and leather using a solar tunnel dryer and Erenturk and Erenturk [30] concluded that ANN prediction of drying characteristics is better than genetic algorithms. More recently Khazaei et al. [35] developed a ANN model for grape drying and it had better performance than multiple regression models and might be useful for automatic control systems for hot air dryers.

Classical mathematical modeling is still the basic tool for performance prediction of agricultural and industrial dryers. Although a mathematical model is available for simulation of solar greenhouse dryers [33], the model is relatively complicated and it is not for litchi flesh. Recently, an alternative and a qualitatively new tool for solving ill-posed, complex processing problems has been developed – artificial neural network (ANN) technique– and this enables the conduction of very fast and simple simulations. The technique does not require the formulation of an analytical description. Instead, a black-box model is constructed and exposed to carefully selected data to train the model for prediction of the performance. No study has been reported on ANN modeling of litchi and the previous work [29] on solar drying of jackfruit bulbs and leather in a solar tunnel dryer is not applicable to litchi due to the fact that the ANN is based on data and input-output analysis.

In terms of the performance of a parabolic greenhouse solar dryer, the performance of this type of dryer for drying banana, longan and chili has been investigated [36, 37]. However, the experimental performance of drying litchi flesh has not been reported. Therefore, the objectives of this work are to investigate the performance of the parabolic greenhouse solar dryer for drying litchi flesh and to perform ANN modeling of this dryer for drying litchi flesh.

2. Methodology

2.1 Experimental performance of solar drying of litchi flesh in the parabolic greenhouse dryer

2.1.1 Description and working principle of the dryer

The parabolic greenhouse solar dryer in this investigation consists of a parabolic roof structure made from polycarbonate sheets on a concrete floor. The structure of the dryer is made of galvanized iron bars. The products to be dried are placed as a thin layer on four arrays of trays. Polycarbonate sheet was selected to be the transparent cover of the dryer, because it has high transmittance (0.8) in shortwave solar radiation and low infrared transmittance (about 0.2), thus creating the greenhouse effect in the dryer. Three DC fans operated by a 50-W solar cell module were installed in the wall opposite to the air inlet to ventilate the dryer. With this solar cell module, the dryer can be used in rural areas without access to electricity grids. The parabolic cross-sectional shape helps to reduce wind load and a pictorial view of the dryer used in this study is shown in Fig. 1. The structure and dimension of the dryer are depicted in Fig. 2.

Solar radiation passing through the polycarbonate roof heats the products being dried on the trays, the concrete floor and all solid parts inside the dryer. Ambient air is drawn in through a small opening at the bottom of the rear side of the dryer and is heated by the floor and all parts inside the dryer. Heated air, while passing through and over the product, transfers its thermal energy to the product by convection, causing water evaporation and moisture transfer from the product to the air. This moist air is sucked from the dryer by three 14-Watt PV fans located at the top of the front side of the dryer.

Fig. 1 Pictorial view of the parabolic greenhouse solar dryer.

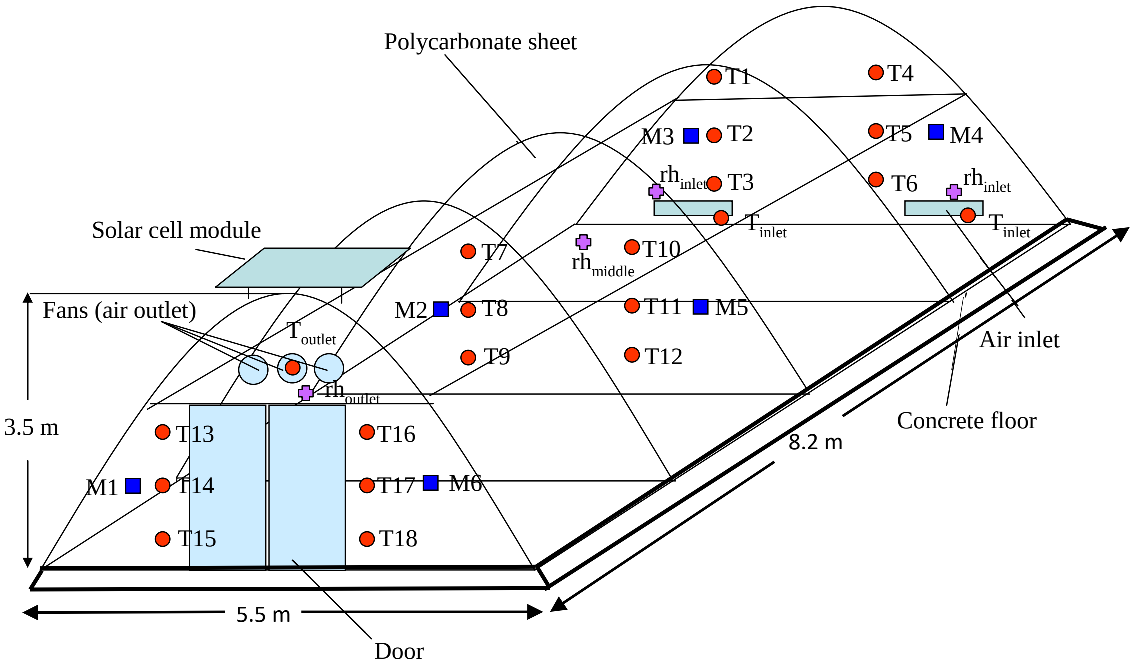

Fig. 2 The structure and dimensions of the dryer and the positions of the thermocouples (T), hygrometers (rh), and product samples for moisture content determining (M).

2.1.2 Experimental procedure

Litchi was dried in the parabolic greenhouse solar dryer installed at Silpakorn University (13.82° N, 100.04°), Nakhon Pathom, Thailand. A total of ten experiments were conducted during three harvest seasons of litchi in 2008, 2009 and 2015. It is to be noted that normal litchi harvest season lasts about 3 months (April-June). To monitor the performance of the dryer, various sensors were installed in the dryer. Solar radiation was measured by a pyranometer (Kipp & Zonen, model CM 11, accuracy ± 0.5%) placed on the roof of the dryer. Temperature was measured by using K-type thermocouples. Hot wire anemometers (Airflow, model TA5, accuracy ± 2%) were used to monitor the air speed at the air outlet of the dryer. Another anemometer was also used to monitor the ambient wind speed. The relative humidity of ambient air and drying air was periodically measured by hygrometers (Electronik, model EE23, accuracy ± 2%). The positions of these measurements are shown in Fig. 2. Voltage signals from the pyranometer, hygrometers and thermocouples were recorded every 10 minutes by a multi-channel data logger (Yokogawa, model DC100). For each drying test, 100 kg of litchi flesh was used. The experiments were started at 8.00 am and continued till 6.00 pm. Litchi flesh was kept in the dryer during night time and the drying was continued until the desired moisture content of 12% (wet basis) was reached. The final moisture content corresponds to the moisture content of high quality dried products in local markets. Product samples were placed in the dryer at various positions (Fig. 2) and were periodically weighed at 1-hour intervals using a digital balance (Kern, model 474-42, accuracy ± 0.1 g). Also, samples of about 100 g of the fresh product were placed outside the dryer and the mass was monitored at 1-hour intervals. The moisture contents of the products inside the dryer were compared against the control samples (open-air natural sun dried) dried outside the dryer. The moisture content during drying was estimated from the weight of the product samples and the dried solid mass of the samples. At the end of the experimental drying run, the exact dry solid mass of the product samples was determined by the oven method (103°C for 24 hours).

2.1.3 Measurement of the colour of dried product

The colour of solar dried litchi was measured by chromometer (Hunter Lab, Miniscan XE plus) which provides the colour according to Commission Internationale l'Eclairage (CIE) chromaticity coordinates. The parameter L* is a measure of lightness (L*=0 for black, L*=100 for white), a* is an indicator of redness (a*>0 for red, a*<0 for green) and b* is an indicator of yellowness (b*>0 for yellow, b*<0 for blue). The L*a*b* [38-39] and L*C*h [40] colour systems were selected for this work because these are the most-used systems for evaluation of the colour of dried food materials. The instrument was standardized each time with a white ceramic plate. Three readings were taken at each place on the surface of samples and then the mean values of L*, a* and b* were averaged. The different colour parameters were calculated using the following equations [40]:
Hue angle (h) indicating colour combination is defined as:

$$h = \begin{cases} \tan^{-1}(b^*/a^*) & (\text{when } a^* > 0) \\ 180^\circ + \tan^{-1}(b^*/a^*) & (\text{when } a^* < 0) \end{cases} \tag{1}$$

and chroma (C*) indicating colour intensity or saturation is defined as:

$$C^* = (a^{*2} + b^{*2})^{1/2} \tag{2}$$

2.2. Artificial neural network (ANN) modeling

The methods of system modeling and identification are fundamental both for explanation of naturally occurring phenomena and for designing man-made engineering processes [24]. For the drying process, classical mathematical modeling such as using a partial differential equation model is still the basic tool used for process description. In spite of unquestionable advantages in using the mathematical process modeling approaches i.e. the equation for drying rate, there are also disadvantages that are often difficult to overcome. These include, among others, the necessity to determine many process state parameters like kinetic coefficients and physicochemical characteristics of a material and the drying agent. The costs involved in the experimental determination of these coefficients frequently diminish the advantages that can be gained from development of a mathematical model of the process. ANN techniques, by their nature, can overcome these problems, and thereby open new pathways in approaching a model design problem of this sort. However, in the literature, there are a few studies concerning mathematical modeling of the drying process by means of ANN. In addition, there is a hybrid modeling approach that combines an ANN model with a mathematical model. These types of models, however, are limited.

The neuro-computing techniques are shaped after biological neural functions and structures. Thus, they are popularly known as ANN. Similarly, as for their biological counterparts, the functions of ANN are being developed not by programming them, but by exposing them to carefully selected data on which they can learn how to perform the required processing task. In such a modeling approach, there is no need to formulate an analytical description of the process. Instead, a black-box process model is constructed by interacting the network with representative samples of measurable quantities that characterize the process.

2.2.1 Structure of ANN model of the parabolic greenhouse solar dryer

Artificial neural networks are biologically inspired; they are composed of elements that perform in a manner that is analogous to the most elementary functions of the biological neuron. The artificial neuron is designed to mimic the first order characteristics of the biological neuron. In essence, a set of inputs are applied, each representing the output of another neuron. Each input is multiplied by corresponding weight and all of the weighted inputs are summed to determine the activation level of neurons. The summed body corresponds to the biological cell body producing an output. The simplest network is a group of neurons arranged in a layer and multilayer networks are formed by simply cascading a group of single layers, the output of one layer provides the input to subsequent layers.

An independent multilayer ANN model of the parabolic greenhouse solar dryer was developed to represent the drying system of litchi flesh. Although the equation for predicting the drying rate of litchi flesh is available [41], the ANN does not require such equation. The ANN model developed for litchi flesh has a four-layered network, which has a large number of simple processing elements called neurons (Fig. 3). The input layer of the model consists of four neurons that correspond to the four input variables, while the output layer has one neuron that represents the moisture content (MC) in the model. The input variables are: (1) time (t); (2) solar radiation (I_t); (3) temperature at the middle of the dryer (T) and (4) airflow rate ($\dot{m}$). I_t, T and ($\dot{m}$) were obtained from measurements. These three variables varied with time and their values from the measurements were used as input data of the ANN.

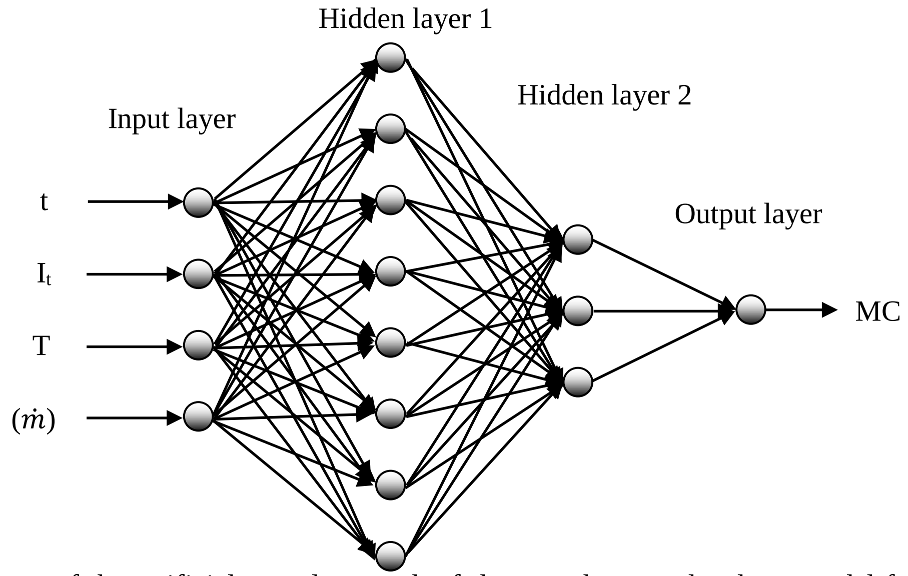

Fig. 3 The structure of the artificial neural network of the greenhouse solar dryer model for drying litchi: t is time (hour), I_t is solar radiation (W/m^2), T is drying air temperature at the middle of the dryer (°C), ($\dot{m}$) is air flow rate (m^3/h) and MC is moisture content (%, wb).

The use of a number of hidden layers in the ANN depends on the degree of the complexity of the problem [31, 42-44] and on the application of the network [25]. There are no fixed rules for determining the number of hidden layers and nodes [35]. In general, one hidden layer has been found to be adequate, but in some cases a slight advantage may be achieved using two hidden layers [45]. Therefore, the number of hidden layers used was two. Larger number of neurons can represent the system more precisely, but complication arises to attain proper training [46]. After evaluating a large number of ANN, the number of neurons in hidden layers 1 and 2 of the model were found to be 8 and 3, respectively. All inputs were normalized between the values of 0.00 to 1.00. In this study the learning rate was initially set at 0.1 but finally reduced to (0.01) and momentum was chosen to be 0.7 in order to prevent over training. The networks were trained for a fixed number of 1000 cycles and the minimum value of root mean square error was always achieved. The performances of the ANN models were compared using the root mean square error (RMSE), the square of correlation coefficient or coefficient of determination, r^2. All the trials were conducted using a computer program written in C^{++}. The program used values of moisture content, solar radiation and flow rate obtained from measurements as its input data and these varied with time.

2.2.2 Training of the ANN model

ANN can modify their behavior in response to their environment. This factor, more than any other, is responsible for the interest they have received. Unlike a mathematical model, the structure of an ANN model itself cannot represent the system behavior, unless it is properly trained. The objective of training the network is to adjust the weights of the interconnecting neurons of the network so that application of a set of inputs produces the desired set of outputs. Initially, random values were used as weights and it was set to be 1.0. For brevity, one input–output set can be referred to as a vector. Training assumes that each input vector is paired with a target vector representing the desired output; together these are called a training pair. Usually, a network is trained over a number of training pairs.

A wide variety of training algorithms has been developed, each with its own strength and weakness. The ANN dryer models are trained by the back propagation algorithm so that the application of a set of inputs would produce the desired set of outputs [27]. The steps of the training procedure are summarized as follows: (1) an input vector is applied; (2) the output of the network is calculated and compared to the corresponding target vector; (3) the difference (error) is fed back through the network; and (4) weights are changed according to an algorithm called the delta rule [47] that tends to minimize the error. The vectors of the training set are sequentially applied. This procedure is repeated over the entire training set for as many times as necessary until the error is within some acceptable criteria, or until the outputs did not significantly change anymore. After the end of training, simulations are done with the trained model to check the accuracy of the training achieved. In this work, this procedure and the experimental input values were used in the simulation.

3. Results and Discussion

3.1 Experimental performance of the parabolic greenhouse dryer

Ten tests of the dryer for the drying of litchi flesh were performed during three harvest seasons of litchi, namely 2008, 2009 and 2015. Typical results for the drying of litchi flesh are shown in Figs 4-8. Fig. 4 shows the variations of solar radiation during a typical experiment of solar drying of litchi flesh in the parabolic greenhouse dryer. Maximum solar radiation is 1,222 W/m^2 during the drying.

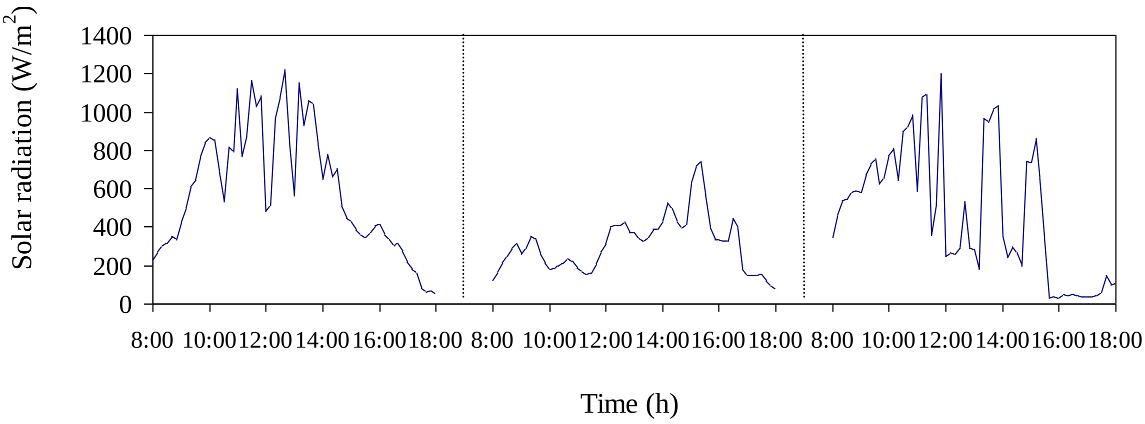

Fig. 4 Variations of the solar radiation during the drying of litchi flesh.

Fig. 5 shows the comparison of air temperatures at three different locations inside the dryer, namely front, middle and back, for a typical experiment of solar drying litchi flesh. Temperatures at different positions in these three locations varied within a narrow band. In addition, temperature at each of the locations significantly differed from the ambient air temperature.

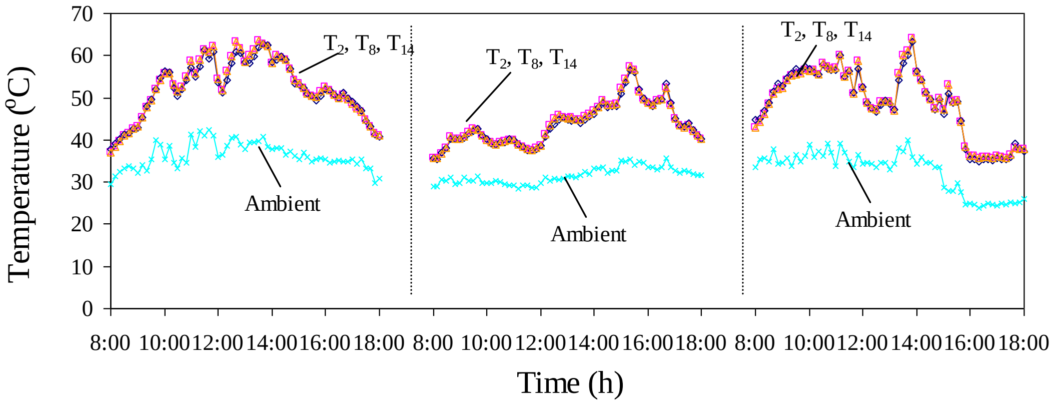

Fig. 5 The variations of the temperatures at different positions inside the dryer.

Fig. 6 shows air flow rates of a typical experiment during the drying of litchi flesh. The airflow rate increases sharply in the early part of the day, then becomes fairly constant and then drops sharply in the afternoon. The pattern of changes in airflow rate follows the pattern of the changes of solar radiation (Fig. 4), since the airflow is regulated by three fans powered by a solar cell module. The maximum air flow rate is 950 m^3 /h.

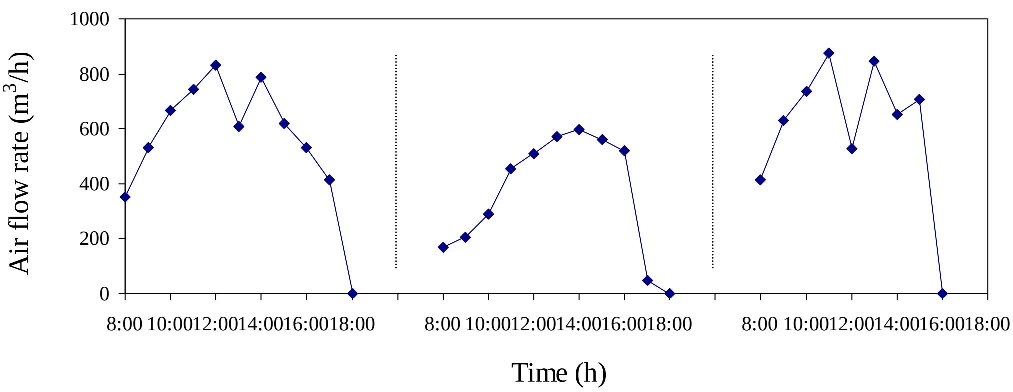

Fig. 6 Variations of air flow rate inside the dryer during drying of litchi flesh.

Fig. 7 shows the variations of moisture content of litchi flesh samples in the dryer for a typical experiment compared to the control sample dried by open-air natural sun drying. The moisture content of the litchi flesh in the solar dryer was reduced from an initial value of 84% (wb) to a final value of 13% (wb) within 3 days whereas the moisture content of the natural sun-dried samples was reduced to only 25% (wb) within the same period. The drying time of litchi flesh in the dryer was significantly reduced to 3 days as compared to 5-6 days in natural sun drying. Thus, the drying rate of litchi flesh dried in the dryer is higher than that dried by natural sun drying. This is because the litchi flesh in the dryer received energy both from direct exposure to solar radiation and heated air in the dryer, however the litchi flesh dried with natural sun received only incident solar radiation and part of the received energy was lost, especially by wind.

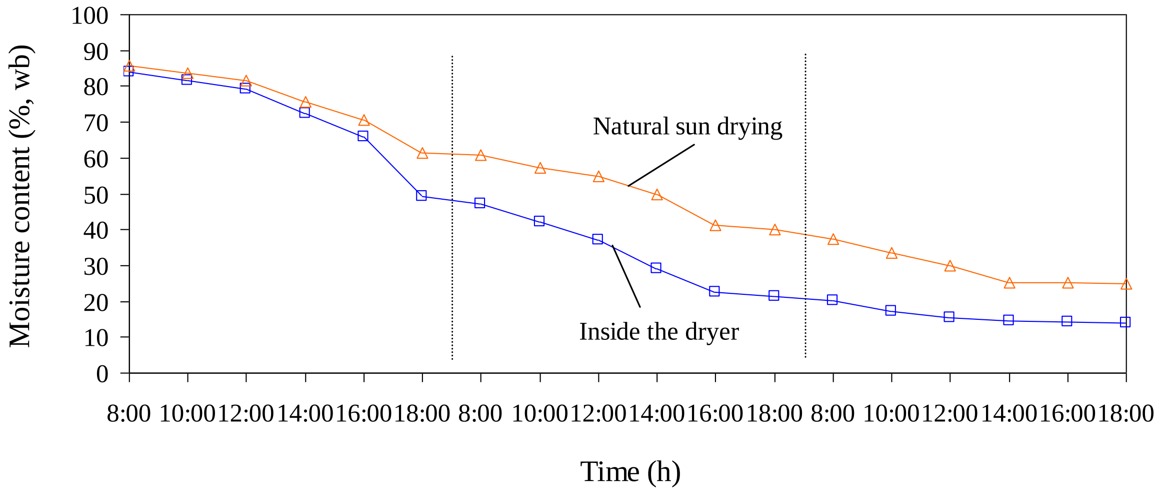

Fig. 7 Variations of the moisture contents (M) during the drying of litchi flesh.

It is interesting to investigate the heat losses from the dryer to surrounding environments, based on the typical experimental results. The analysis of heat losses was undertaken as follows.

The heat losses from the dryer consist mainly of four parts. The first part is the heat loss from the polycarbonate cover to ambient air due to convection ($Q_{conv,c\text{-}a}$), the second part is the heat loss from the cover to the sky due to radiation ($Q_{rad,c\text{-}sky}$), the third part is the heat loss from the floor of the dryer to the ground due to conduction ($Q_{cond,f\text{-}g}$) and the last part is the heat loss due to the out-flow of drying air from the dryer to the surroundings (Q_{flow}). The total heat losses (Q_{total}) can be written as:

$$Q_{total} = Q_{conv,c\text{-}a} + Q_{rad,c\text{-}sky} + Q_{cond,f\text{-}g} + Q_{flow} \tag{3}$$

Heat losses from medium i to medium j (Q_{i-j}) by convection, radiation and conduction for each day, was calculated from:

$$Q_{i-j} = \int_{8am}^{6pm} \dot{Q}_{i-j}\,dt \tag{4}$$

where $\dot{Q}_{i-j}$ is the rate of heat transfer between medium i and j.

The values of $\dot{Q}_{i-j}$ by convection and conduction were estimated by:

$$\dot{Q}_{i-j} = A_{ij}h(T_i - T_j) \tag{5}$$

where A_{ij} is the area of the medium where the heat transfer takes place, h is the heat transfer coefficient and T_i and T_j are temperatures of medium i and j, respectively. The heat transfer coefficients by convection and conduction and the rate of heat loss by radiation was calculated using the method described in Duffie and Beckman [48]. The heat loss Q_{flow} was estimated from the rate of the out-flow of the enthalpy of the drying air from the dryer [49]. Afterward, the heat losses for each day were summed up over the entire drying period to obtain the total heat loss.

Based on the typical experimental results, Q_{total}, $Q_{conv,c-a}$, $Q_{rad,c-sky}$, $Q_{cond,f-g}$ and Q_{flow} were estimated to be 1962.0, 513.4, 597.5, 582.3 and 268.8 MJ, respectively. The total solar radiation incident on the dryer during the entire period of the drying is 3868.5 MJ. Considering the total heat losses and the total solar radiation incident on the dryer, the dryer performed fairly well.

3.2 Colour of dried litchi

The quality of dried litchi flesh was evaluated. The colour of the dried litchi flesh was measured using a chromometer (Hunter Lab, Miniscan XE Plus) and the results are shown in Table 1. The values of the colour indices indicate that the colour of dried litchi is bright yellow reddish. Although the colour intensity was moderate, the colour combination was high. The colour of dried litchi flesh is comparable with high quality dried litchi flesh in markets.

Table 1 Colour of solar dried litchi flesh.

Status	Colour Value				
	L*	a*	b*	C*	h
Solar dried litchi flesh	37.90	6.83	11.38	13.46	58.69

3.3 Performance prediction by ANN model

The artificial neural networks trained with experimental data representing the characteristics of drying litchi flesh should achieve a higher generalization ability. Thus, the experimental data of 7 sets were used for training to construct the models and the data of another 3 sets were reserved for testing the predictive capability of the models. The ANN model of the parabolic greenhouse dryer developed for drying litchi flesh was trained with field-level experimental data. After 1000 cycles of training, the square sum of difference (error) between the observed and the predicted output reached a significantly low level (0.05). Using the trained model, simulations were conducted to check the performance of the model. All the input variables, except moisture content (MC) of the training pairs, were used in the simulation so that the comparison can be done between the observed and the simulated output. The MC value in the simulation was similar to that of the observed one. For every step of the calculation, the output value (FMC) was used as the input value (IMC) in the next step. The comparison between the observed and simulated drying performances of the litchi flesh for the test data is shown in Fig. 8 and Fig. 9. From these figures, it was found that the agreement between the predicted and the observed moisture contents for the litchi flesh is very good. For the selected ANN model, root mean square difference (RMSD) and coefficient of determination (r^2) were 8.7-10.8% and 0.98-0.99, respectively. Judging from the method and equipment involved in the determination of moisture content, the moisture content from the experiment is not more than 5%. The agreement between the moisture content from the experiments and that from the ANN was within the acceptable limits [50]. Thus, if the model is adequately trained, it can appropriately represent the performance of the parabolic greenhouse dryer for drying litchi flesh, and can predict very well the moisture content at any time during drying. Several studies [51-53] reported the use of the ANN models for process control and predictive optimal control and the ANN model developed in this study can be used for process control and predictive optimal control of the greenhouse solar dryers for efficient production of quality dried products.

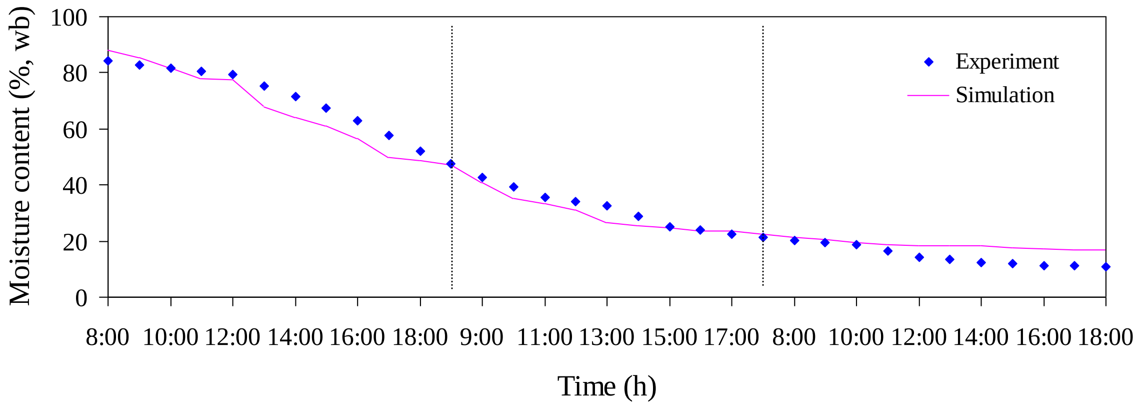

Fig. 8 Comparison of the simulated and observed moisture content during the drying of litchi flesh between 29-31 May 2009 (RMSD = 10.8%).

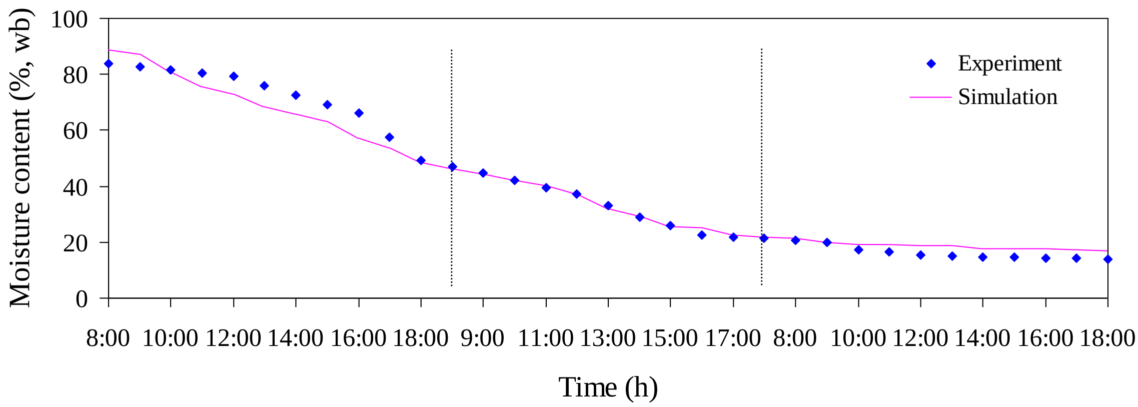

Fig. 9 Comparison of the simulated and observed moisture content during the drying of litchi flesh between 10-12 June 2009 (RMSD = 8.7%).

4. Conclusion

Solar drying of litchi flesh was conducted in the parabolic greenhouse solar dryer. Solar radiation followed similar patterns for all days during drying. Moisture content of the litchi flesh was reduced from an initial value of 84 % (wb) to the final value of 13 % (wb) within 3 days. The dryer can be used to dry up to 100 kg of litchi flesh. In all the cases, the use of this dryer led to considerable reduction in drying time in comparison to that of natural sun drying, and the products dried in the dryer were of good quality. Considering the heat losses and the solar radiation input, the dryer performed fairly well. An ANN approach is used to predict the performance of the dryer, and the model was trained using the solar drying data of litchi flesh. An ANN with four inputs, one output and two hidden layers was found to be able to predict the operation of the dryer after it was adequately trained. The prediction of the model is very good.

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