PERFORMANCE OF THE SOLAR DRYER AND MOISTURE CONTENT PREDICTION OF SWEET TAMARIND USING AN ANN

Jagrapan Piwsaoad* and Chayapat Phusumpao

Abstract

This research presents the experimental performance of solar dryers and artificial neural network modeling of solar dryers for drying sweet tamarinds. Fifteen batches of sweet tamarinds were drying; for each batch, we used 2.0 kilograms of sweet tamarinds. The parameters used in the artificial neural network model are solar radiation, air temperature, relative humidity and airflow rate. The numerical solution was programmed in C^{++}. The results showed that the moisture content, calculated from the model corresponds to the measured values *RMSE*=0.5013 and R^2=0.9818.

Keywords: Solar dryer, Artificial neural network modeling, Sweet tamarind

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Introduction

Thailand is one of the Southeast Asia countries that has many kinds of fruits all year round. Tamarind (*Tamarindusi ndica L.*) is one of the country's GI (Geographical Indication) plants, especially in the northern part. Phetchaboon province (Sweet tamarind city) is famous for growing sweet tamarind. There are wide varieties of sweet tamarind in Thailand, namely Sithong, Prakaithong, Sichomphu, Inthaphalam, Siphakdi and Khanti. In November of every year, sweet tamarind will be sold in the market. However during that time, the relative humidity of the air was high, resulting in fungal inside the tamarind fruit. In many countries, agricultural products are dried under the open sun. However, this way of drying degrades the quality of the dried products due to interference from external impurities and uneven drying rates. Numerous types of solar dryers have been designed and developed in various parts of the world, yielding varying degrees of technical performance. Drying is produced successfully even under unfavorable weather conditions. In the solar mode of operation, these are the most cost-effective types of dryers and are easy to fabricate and use. With this open sun method, substantial losses of sweet tamarind due to insects, animals and rain usually occur during drying. To overcome this problem, well performed dryers are needed to dry sweet tamarinds. In the tropics, Thailand receives abundant solar radiation (Janjai et al., 2005). Consequently, the use of solar dryers for sweet tamarin drying is reasonable, although several types of solar dryers have been developed in the last 50 years (Funholi et al., 2010; Janjai et al., 2007; Janjai et al., 2009; Murthy, 2009; Sharma et al., 2009). They could not meet the high demand for sweet tamarind drying. 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 (Kaminski et al., 1998). Developed an 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 (Khazaei et al., 2013).

As a result, our research group has developed the solar dryer to dry agricultural products. It was successfully used for drying fruits and vegetables. However, it has not been tested to dry sweet tamarinds.

Therefore, the objectives of this research were to investigate the performance of the solar dryer for drying sweet tamarinds (In this research, the performance of the solar dryer is expressed by the thermal efficiency of the solar dryer and the moisture content of the product.) and to develop an ANN model to predict the moisture content of sweet tamarinds.

Materials and Methods

1. Experimental setup

The solar dryer was installed in Loei Province, Thailand. The dryer consists of a polycarbonate sheet on a metal sheet floor. The dimension of the dryer is 2.0 m in width, 3.0 m in length and 2.0 m in height. To ventilate the dryer, two DC fans operated by 10-W solar cell modules were installed in the wall opposite the air inlet. Two 300W heaters powered by AC electricity are installed inside the solar collector. One biomass stove uses rubber wood as fuel; heaters and biomass stoves are only used for drying at night. The solar dryer and measuring points, sweet tamarinds inside the dryer and sweet tamarinds samples outside the dryer are shown in Figures 1 and 2.

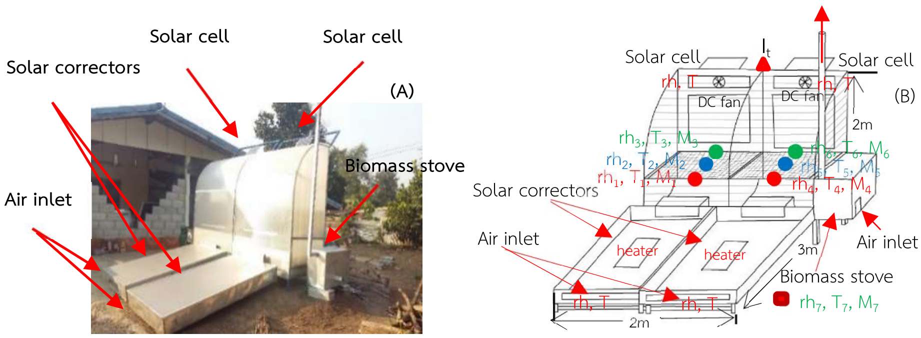

Figure 1 A) Solar dryer and B) Measuring point

Figure 2 (A) Sweet tamarinds inside the dryer; tray1
(B) Sweet tamarinds inside the dryer; tray2
(C) Sweet tamarinds outside the dryer

Solar radiation passes through the polycarbonate roof and heats the product in the dryer and the metal sheet floor. There are 2 solar collectors connected to the front of both dryers and a biomass stove connected to the side of dryers to increase the temperature of the dryers. Ambient air is drawn in through an air-inlet at the bottom of the front side of the dryer and is heated by the floor and the products are exposed to solar radiation. Direct exposure to solar radiation of the products and the heated air enhances the drying rate of the products. Moist air passing through and over the products is sucked from the dryer by the fans at the top of the rear side of the dryer.

2. Experimental Procedure

In this study, sweet tamarinds were dried inside the solar dryer to investigate the dryer potential. The experimental runs were conducted from November 2022 to January 2023. Solar radiation was measured by a pyranometer (Kipp & Zonen model CMP 3, accuracy ± 0.5%) placed on the roof of the dryer. Thermocouples (K type) were used to measure air temperatures in the different positions of the dryer (accuracy ± 2%). A hot wire anemometer (Airflow, model TA5, accuracy ± 2%) was used to monitor the air speed at the inlet and outlet of the dryer. The relative humidity of ambient air and drying air were periodically measured by hygrometer (Electronnik, model EE23, accuracy ± 2%). Fifteen batches of drying test were carried out. For each batch, 2.0 kilograms of sweet tamarinds were placed on the trays inside the dryer. Each day, the experiment was started at 8:00 a.m. and lasted until 6:00 p.m.. The drying was continued on subsequent days until the desired moisture content was reached. Product samples (200 g) were placed at various positions inside and outside the dryer (open sun dry). They were weighed periodically at two-hour intervals using a digital balance (Kern, model 474 – 42). At the end of the experimental drying, the exact dry solid weight of the product samples were determined by the oven method (103 °C for 24 hours, accuracy ± 0.5%). The moisture content during drying was estimated from the weight of the product samples and the estimated dried solid mass of the samples.

4. The thermal efficiency of the solar dryer

The thermal efficiency was calculated from the drying rate to the energy yield rate for sweet tamarinds drying is determined by:

$$\eta_{solar} = \frac{\dot{m}_w h_{fg}}{A_{solar} I_t} \times 100\ (\%) \tag{1}$$

Where η_{solar} is the thermal efficiency (%); $\dot{m}_w$ is the evaporation rate of water (kg/s); h_{fg} is the latent heat of vaporization of water (kJ/kg); I_t is the total radiation incident on the dryer (W/m^2); A_{solar} is the solar radiation area of the dryer (m^2).

4. Structure of neural network model

The neurocomputing techniques are shaped after biological neural functions and structures. Therefore, they are popularly known as artificial neural networks. Similarly, as for their biological counter parts, 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 analytical description of the process.

The perceptron is a simple neuron model that takes input signals (patterns) coded as (real) input vectors (input data) through the associated (real) vector of synaptic weights. The output n is determined by:

$$n = \sum_{i=1}^{N} w_i x_i. \tag{2}$$

Where n is net denotes the weighted sum of inputs, w_i is synaptic weights and x_i input vectors (input data). As has already been mentioned, the activation functions need to differentiable and are usually of the sigmoid shape. The most common activation functions are:

$$f(x) = f(n) = \frac{1}{(1+e^{-n})}. \tag{3}$$

Where f is the activation function. Instead, a black-box process model is constructed by interacting the network with representative samples of measurable quantities characterizing the process (Piwsaoad, 2019). An independent multilayer ANN model for moisture content of sweet tamarinds is developed shown in Figure 3.

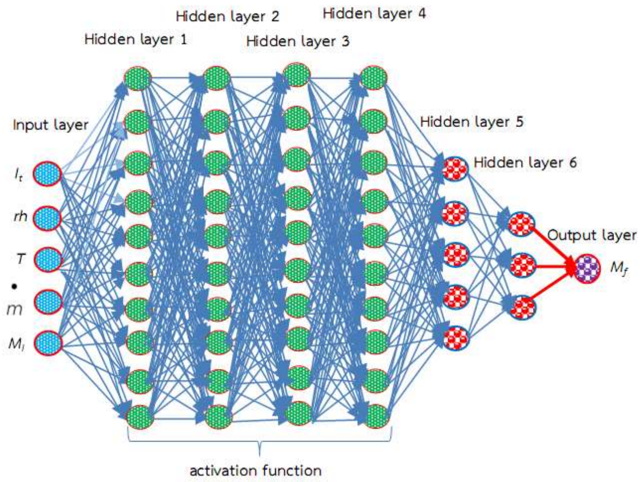

Figure 3 The structure of the artificial neural network

The neural networks with various structures were investigated, including eight layers with different number of neurons in each hidden layer, different values of learning rate and momentum. The input layer of the model comprises of five neurons which correspond to solar radiation (I_t), airflow rate ($\dot{m}$), air relative humidity (rh), air temperature (T) and initial moisture content (M_i). The output layer has one neuron which represents the final moisture content (M_f). A selection of the number of neurons for hidden layers is optional. A large number of neurons can represent the system more precisely, but obtaining proper training for the network is more complicated. In this work, the selected number of neurons in hidden layer 1, 2, 3 and 4 of the models are 10; the selected number of neurons in hidden layer 5 of the models are 5 and hidden layer 6 are 3, respectively (Janjai et al., 2015).

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. 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 total of 30 training pairs were used to train the model, which were the observed data obtained from 14 independent experimental runs. The ANN drier models are trained by a backpropagation algorithm so that applying a set of inputs would produce the desired set of outputs. The vectors of the training set are applied sequentially. This procedure is repeated over the entire training set as many times as necessary until the error is within some acceptable criteria, or until the outputs do not significantly change any more. After the end of training, simulations were done with the trained model to check the accuracy of the model. Experimental input values were used in the simulation. The artificial neural network model was programmed in C^{++}.

5. **Performance analysis**

Statistical parameters were used for performance analysis. Root mean square error (*RMSE*) and determination coefficient (R^2) of agreement were computed to estimate the overall model performance. These are defined as:

$$R^2 = \frac{1-Residual\ sum\ of\ squares}{Corrected\ total\ of\ squares} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(MR_{pre,i}-MR_{mea,i})^2}{n}}. \tag{5}$$

Where $MR_{pre,i}$ is the predicted moisture contents; $MR_{mea,i}$ is the measured moisture contents; i = 1–N; N is the number of observations; *RMSE* and R^2 are the two most commonly used statistical parameters, which represent the degree of explanation and the average difference between estimated and observed values. Values of R^2 close to 1 with small values for the error terms are desirable (Piwsaoad & Phusumpao, 2021).

Result

1. **Drying characteristic of sweet tamarinds**

Drying experiments of sweet tamarinds in the solar dryer were carried out from November 2022 to January 2023. The experimental results are shown in Figure 4.

Solar radiation from Figure 4 (A), shows that the solar radiation does not fluctuate due to the clear sky. The variation of solar radiation with time of the day during the drying of sweet tamarinds varied from 138 – 720 (W/m^2).

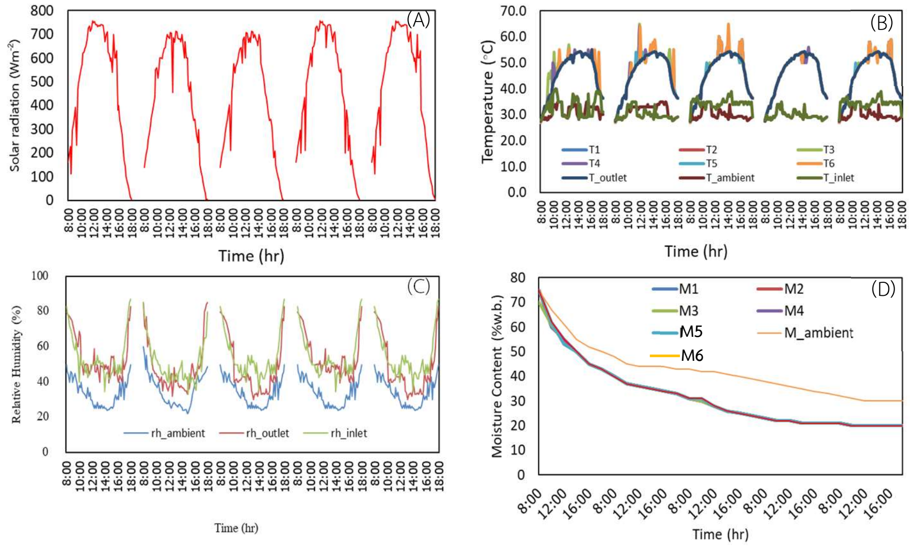

Figure 4 (A) Variation of solar radiation with time of the day during drying

(B) Variation of temperature at different positions during drying

(C) Variation of relative humidity with time of the day during drying

(D) moisture content of sweet tamarinds during drying

In Figure 4 (B), the patterns of temperature change in different positions were comparable for all positions. The variation of ambient temperature and the temperature at different positions inside the solar dryer during the drying of sweet tamarinds varied from 29 - 65 (°C).

In Figure 4 (C), relative humidity decreased over time at different positions inside the dryer during the first half of the day while the opposite is true for the other half of the day. The variation of relative humidity with time of the day during the drying of sweet tamarinds varied from 22.0 – 85.0 (%).

In Figure 4 (D), the comparison of moisture content at different positions inside the dryer and the open sun drying for the experimental runs of solar drying of sweet tamarinds. The moisture contents of sweet tamarinds inside the solar dryer were reduced from an initial value of 75.0% (w.b.) to a final value of 20.0% (w.b.) within 5 days. In contrast, the moisture contents of the open sun-dried samples were reduced to 40.0% (w.b.) in the same period.

The variation airflow rate with time of the day during the drying of sweet tamarinds varied from 25 – 1,200 (m^3/s).

2. **The thermal efficiency of the solar dryer**

The thermal efficiency of the solar dryer of sweet tamarinds are shown in Figure 5.

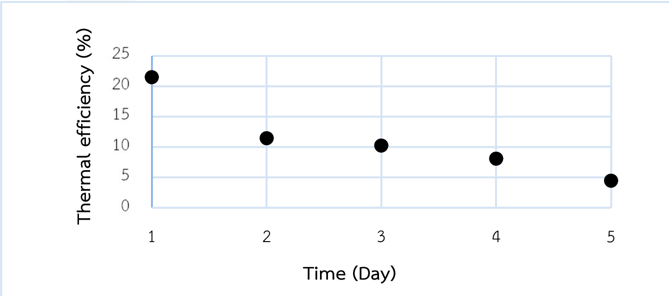

Figure 5 Thermal efficiency of the solar dryer

The thermal efficiency of the solar dryer for sweet tamarind drying, calculated per day, was found to be between 4.4-21.4%.

3. **Performance prediction by ANN model**

The ANN models of the solar dryer developed for sweet tamarinds drying were trained with the experimental data from fourteen experiments. The data from the fifteen experiments were reserved for the testing the model.

Before training, a certain preprocessing steps on the network inputs and targets to make more efficient neural network training was performed. The produced experimental data sets (a total of 30) were randomized, where 14 patterns were randomly selected by the software to be used for testing an ANN model. The sigmoid transfer function of neuron activation in the hidden layers was chosen. Prior to their use in the model, the input and the output values were normalized.

After 100,000 times of iteration steps of training, the square sum of difference (error) between the measured and the predicted output reached a significantly low level. The comparison between the predicted and measured moisture contents of the dryer are shown in Figure 6, and the training and testing data are shown in Table 1.

Table 1 Training and Testing data

Phase	*RMSE*	R^2
Training	2.4541	0.7151
Testing	0.5013	0.9818

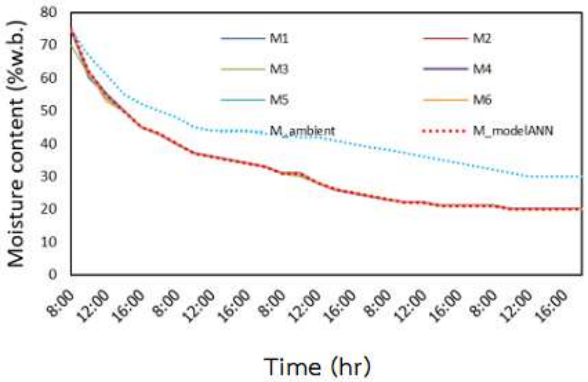

Figure 6 ANN of sweet tamarinds drying

From Figure 6, it was found that the agreement between the predicted versus measured moisture contents is good, the root mean square error (*RMSE*=0.5013), and determination coefficient (R^2=0.9818) with respect to the mean measured value. Thus, if the model is adequately trained, it can appropriately predict the performance of the solar dryer for drying sweet tamarinds.

Discussions

Solar radiation passes through the polycarbonate roof and heats the product in the dryer and the metal sheet floor. Temperatures in different positions varied within a narrow band. In addition, temperatures at each positions differed significantly from the ambient air temperature. Relative humidity decreased over time at different positions inside the dryer during the first half of the day, while the opposite is true for the other half of the day. No significant difference was found between relative humidity of different positions inside the dryer. However, relative humidity was significantly different for all positions inside the dryer compared to the ambient air. The relative humidity of the air inside the dryer was lower than that of the ambient air. The moisture content of sweet tamarinds gradually decreased. From the moisture content decreasing curves of sweet tamarinds at different positions, there was a difference equal to 5% (w.b.). In the last period, the moisture content was almost the same. It indicates that the moisture content drying rate of sweet tamarinds at different positions is quite uniform. Compared to open sun-dried, the moisture content value decreases more slowly.

The thermal efficiency of the solar dryer for sweet tamarinds drying, calculated per day, was between 4.4-21.4%.

An ANN was found to be able to predict the operation of the dryer after it was adequately trained; *RMSE* =2.4541, R^2=0.7151 and after testing, it was found that *RMSE*=0.5013, R^2=0.9818. Demonstrate that the model has received adequate training. Therefore, the efficiency of sweet tamarind drying machine can be predicted appropriately and can be applied to other agricultural products.

In this research after drying, sweet tamarind's moisture content and quality were close to the standard values. Tamarind pulp contains 20% water, 3-3.5% protein, 0.4-0.5% fat, 70% carbohydrates, 3% fiber and 2.1% ash, respectively. Sweet tamarind should have acid content in the form of tartaric acid (tartaric acid) not more than 5%.

The advantage of this dryer is that there are three sources of energy: solar energy, Thermal energy from heaters and energy from biomass. It can be used in all weather conditions and seasons and an ANN can be applied to the dryer or similar work.

Conclusions

Fifteen sets of sweet tamarinds were conducted, and the drying air temperature varied from 29°C to 65°C during drying. This drier can be used to add 2.0 kilograms of fresh sweet tamarinds. The sweet tamarinds dried inside the solar dryer were completely protected from rain, insects and dust. The dried sweet tamarinds were a high-quality product. The performance of the solar dryer for drying sweet tamarinds has been experimentally investigated. It was found that using this dryer led to a considerable reduction in drying time compared to that open sun drying. The moisture content of sweet tamarinds inside the solar dryer was reduced from an initial value of 75.0% (w.b.) to a final value of 20.0% (w.b.) within 5 days whereas as the moisture content of the open sun dried samples was reduced to 40.0% (w.b.) in the same period.

The thermal efficiency of the solar dryer for sweet tamarind drying was tested for 5 days. It was found that day 1 was efficient, and days 2-5 decreased efficiency depending on solar radiation intensity.

An ANN model was found to be able to predict the moisture content after it was adequately trained. An ANN has a predictive power of *RMSE*=0.5013, R^2=0.9818. Within the temperature range investigated, an ANN model can be used to describe moisture content of sweet tamarinds.

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