Rajabhat J. Sci. Humanit. Soc. Sci. 20(1): 97-110, 2019

เครื่องอบแห้งพลังงานแสงอาทิตย์ไฮบริดสำหรับอบแห้งสับปะรด วิสาหกิจชุมชนไร่ม่วง จังหวัดเลย ประเทศไทย

HYBRID SOLAR DRYER FOR DRYING PINEAPPLES OF RAIMOUNG COMMUNITY ENTERPRISE, LOEI PROVINCE, THAILAND

จักรพรรณ์ ผิวสอาด
Jagrapan Piwsaoad

Faculty of Science and Technology, Loei Rajabhat University
corresponding author e-mail: jagrapan25@gmail.com

(Received: 17 July 2018; Revised: 16 November 2018; Accepted: 10 December 2018)

บทคัดย่อ

งานวิจัยนี้ทำการศึกษาสมรรถนะ และแบบจำลองโครงข่ายประสาทเทียมของเครื่องอบแห้งพลังงานแสงอาทิตย์ไฮบริดสำหรับอบแห้งสับปะรดที่วิสาหกิจชุมชนไร่ม่วง จังหวัดเลย (17.48°N, 101.72°E) ประเทศไทย โดยทำการอบแห้งสับปะรดทั้งหมด 10 ชุดการทดลอง แต่ละชุดการทดลองใช้สับปะรด 10.0 กิโลกรัม ตัวแปรที่ใช้ในแบบจำลองคือ ความเข้มรังสีอาทิตย์ อุณหภูมิของอากาศ ความชื้นสัมพัทธ์ของอากาศ และอัตราการไหลของอากาศ หาผลเฉลยเชิงตัวเลขดังกล่าวโดยใช้โปรแกรมภาษา C++ ผลการทดลองพบว่าปริมาณความชื้นของสับปะรดคำนวณจากแบบจำลองสอดคล้องกับผลการวัดที่ได้จากการทดลอง โดยมีค่า *RMSE* = 0.4003 และ R^2 = 0.9918

คำสำคัญ: เครื่องอบแห้งพลังงานแสงอาทิตย์ไฮบริด แบบจำลองโครงข่ายประสาทเทียม สับปะรด

Abstract

This research presents experimental performance and artificial neural network modeling of a hybrid solar dryer for drying pineapples at Raimoung Community Enterprise, Loei province (17.48°N, 101.72°E), Thailand. Ten batches of the pineapples were used for drying experiments, 10.0 kg of the pineapples per batch. The parameters used in the artificial neural network model are solar radiation, air temperature, relative humidity and airflow rate. The numerical solution was programmed using C++ programming. The results showed that pineapple moisture contents calculated from the model corresponded with the experimental values, representing *RMSE*=0.4003 and R^2=0.9918.

Keywords: hybrid solar dryer, artificial neural network modeling, pineapple

Introduction

In 2018, pineapple farmers of Loei province are facing a crisis with prices plunging to new lows, due to oversupply. For the last six months, the markets for pineapples have been showing a downward trend with prices below 3-5 baht per kilogram. Farmers need a minimum of 16-20 baht per kilogram to meet the cost. Average return ranges between 30-40 baht per kilogram even in the peak seasons during August-February. For the last 6 months, markets have been depressed. Some farmers did sell the fruit for only 3-5 baht per kilogram. The pineapple samples are shown in Figure1.

Figure 1 (A) pineapple growing area (B) pineapples price 5 baht per kilogram (C) pineapple price 4 baht per kilogram (D) pineapple price 3 baht per kilogram (E) pineapple samples (F) pineapple fresh cut product

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. Basically, there are three types of solar dryers; direct solar dryer, indirect solar dryer and mixed-mode dryer, or hybrid solar dryer. This paper is focused on hybrid solar dryers. Drying produced successfully even under unfavorable weather conditions. In the hybrid mode of operation, it is the most cost-effective type of dryers as well as easy to fabricate and use.

With the open sun method, substantial losses of pineapple due to insects, animals and rain usually occur during drying. To overcome this problem, well performed dryers are needed to dry pineapples. Situated in the tropics, Thailand receives abundant solar radiation (Janjai et al., 2005). Consequently, the use of solar dryers for pineapple 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; 2009a; 2009b; Murthy, 2009; Sharma et al., 2009). However, they could not meet the high demand of pineapple drying. As a result, our research group has developed a hybrid solar dryer to dry agricultural products. It was successfully used for drying fruits and vegetables. However, it has not been tested for pineapples.

Therefore, the objectives of this research were to investigate the performance of the hybrid solar dryer for drying pineapples, and to develop an artificial neural network (ANN) model to predict the performance of the hybrid solar dryer.

Materials and Methods

1. Experimental setup

The hybrid solar dryer was installed at Loei province, Thailand. The dryer consists of a parabolic roof structure made from polycarbonate sheets on a metal sheet floor. The dimension of the dryer is 1.5 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 to the air inlet. Two 300W heaters were installed in the solar collector for increasing temperature, when the internal temperature is less than 50°C. The positions of all measurements are shown in Figure 2. Hybrid solar dryer, pineapples inside the dryer and pineapple samples (open sun drying) are shown in Figure 3.

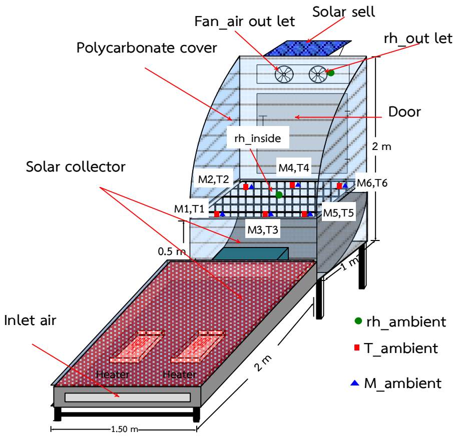

Figure 2 The positions of all measurements in the dryer

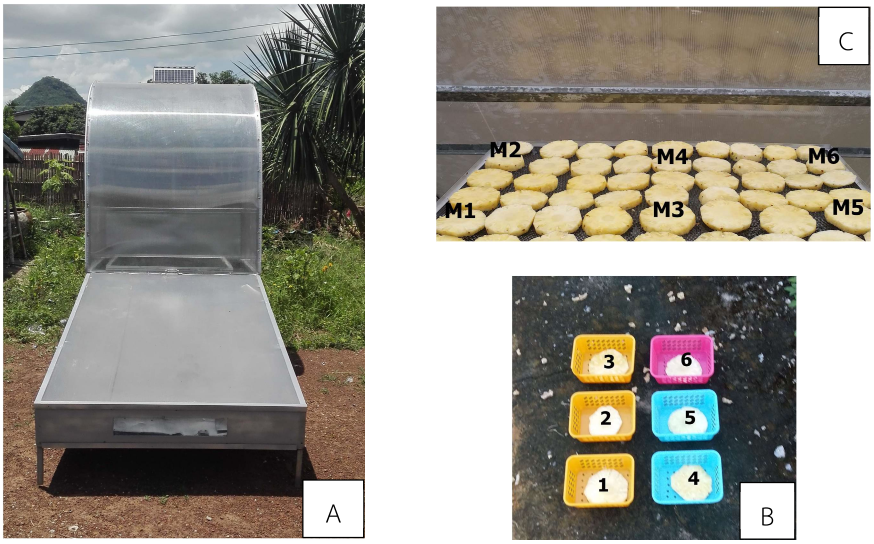

Figure 3 (A) hybrid solar dryer (B) pineapple samples (open sun drying)
(C) pineapples inside the hybrid solar dryer

From Figure 3, solar radiation passing through the polycarbonate roof heats the product in the dryer and the metal sheet floor. 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. Then, the products are exposed to solar radiation. Direct exposure to solar radiation of the products and the heated air enhance 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. Due to the utilization of the PV ventilated system, this type of hybrid solar dryer can be used in rural areas without electricity grids.

2. Experimental procedure

In this study, pineapples were dried in the hybrid solar dryer to investigate the dryer potential. The experimental runs were conducted during January, 2018 - June, 2018. 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%). The positions of all measurements are shown in Figure 2. Ten batches of drying test were carried out. For each batch, 10.0 kilograms of the pineapples were placed on the trays inside the dryer. Each day, the experiment was started at 8:00 am and lasted until 6:00 pm. The drying was continued on subsequent days until the desired moisture content was reached. Product samples were placed at various positions in the dryer and were weighed periodically at two-hour intervals using a digital balance (Kern, model 474 – 42). Product samples about 200 g from the dryer were weighed at two-hour intervals. At the end of the experimental drying, the exact dry solid weight of the product samples were determined by the hot 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.

3. Structure of neural network model

The neurocomputing techniques are shaped after biological neural functions and structures. Therefore, they are popularly known as ANN. 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:

$$n=\sum_{i=1}^{n} w_i x_i \,. \qquad \text{..(1)}$$

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:

$$f(x)=f(n)=\frac{1}{(1+e^{-n})}. \qquad \text{...(2)}$$

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.

An independent multilayer ANN model for moisture content of pineapples are developed and are shown in Figure 4 and Figure 5.

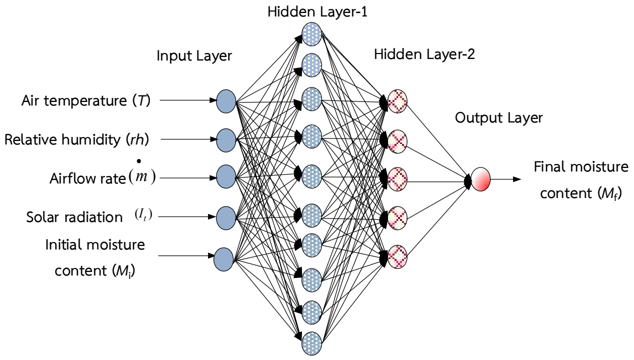

Figure 4 The structure of the artificial neural network (5:10:5:1)

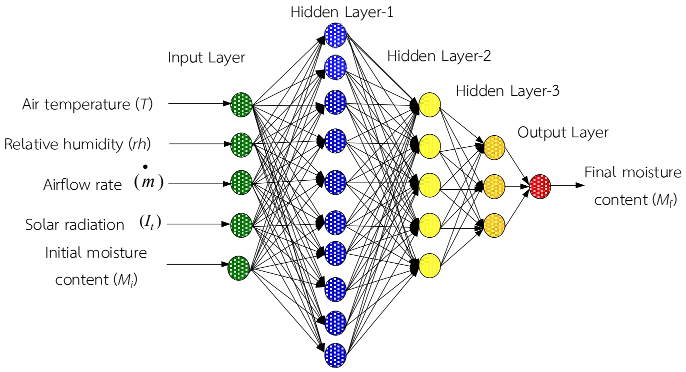

Figure 5 The structure of the artificial neural network (5:10:5:3:1)

The neural networks with various structures were investigated, including 4 and 5 layers with different number of neurons in each hidden layer, different values of learning rate and momentum. The best ANN structure was selected on the basis of the lowest error on the training and verification of ANN. The best ANN model and optimum values of network parameters were obtained by trial and error. The performances of the various ANN configurations were compared using the coefficient of determination (R^2) and the root mean square error, *RMSE*. The input layer of the model comprises of five neurons which correspond to solar radiation (I_t), airflow rate ($\overset{g}{m}$), 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 it is more complicated to obtain proper training of the network. In this work, (model 1) the selected number of neurons in hidden layer 1and 2 of the model are 10 and 5 respectively, (model 2) the selected number of neurons in hidden layer 1, 2 and 3 of the models are 10, 5 and 3 respectively.

ANNs 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 artificial NN model itself cannot represent the system behavior, unless it is properly trained (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 305 training pairs were used to train the model, which were the observed data obtained from 9 independent experimental runs.

The ANN drier models are trained by backpropagation algorithm so that the application of a set of inputs would produce the desired set of outputs. 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 delta rule, that tends to minimize the error.

The vectors of the training set are applied sequentially. 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 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 using C++.

4. Economic analysis

The total capital cost for the hybrid solar dryer (C_T) is given by the following equation, $C_T = C_m + C_l$, where C_m is the material cost of the dryer and C_l is the labor cost for the construction. The annual cost calculation method proposed by Audsley and Wheeler yields (Audsley & Wheeler, 1978; Piwsaoad & Phusampao, 2016) was used.

$$C_{annual} = \left[C_T + \sum_{i=1}^{N} \left(C_{maint,i} + C_{op,i} \right) w^i \right] \left[\frac{w-1}{w\left(w^N - 1\right)} \right]. \qquad \text{..............................(3)}$$

Where C_{annual} is the annual cost of the system. $C_{maint,I}$ and $C_{op,I}$ are the maintenance cost and the operating cost at the year i respectively. w is expressed as

$w=\left(100+i_{in}\right)/\left(100+i_f\right)$; where i_{in} and i_f are the interest rate and the inflation rate in percent, respectively. The operating cost (C_{op}) is the labor cost for operating the dryer ($C_{labour,op}$). The maintenance cost of the first year was assumed to be 1% of the capital cost. The annual cost per unit of dried product is called the drying cost (Z, USD/kg). It can be written as: $Z=\frac{C_{annual}}{M_{dry}}$, where M_{dry} is the dried product obtained from this dryer per year.

$$\text{Payback period}=\frac{C_T}{M_{dry}P_d - M_f P_f - M_{dry}Z}. \qquad \text{(4)}$$

Where M_{dry} is annual production of dry product (kg), M_f is the amount of fresh product per year (kg), P_d is the price of the dry product (USD/kg) and $P_f$is the price of the fresh product (USD/kg).

1. Performance analysis

Three 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:

$$R^2=\frac{1-\text{Re}sidual\ sum\ of\ squares}{Corrected\ total\ of\ squares} \qquad \text{(5)}$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(MR_{pre,\,i}-MR_{exp,\,i})^2}{n}}. \qquad \text{(6)}$$

Where i = 1–N; N is the number of observations; $x_{model,i}$ is the simulated values; $x_{meas,I}$ are the observed values. $RMSE$ 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.

Result and discussion

1. Drying Characteristic of pineapples

Drying experiments of pineapples in the hybrid solar dryer were carried out in 1 January 2018 - 15 June 2018. Ten batches of experimental runs were carried out. The typical results are shown in Figure 6-10.

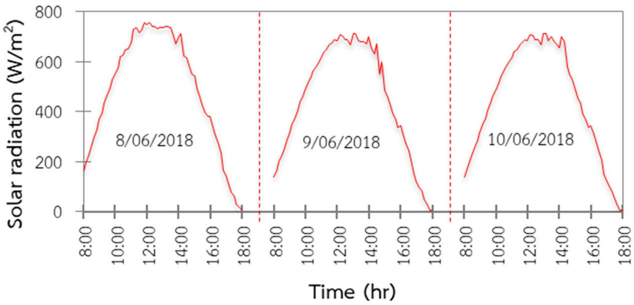

Figure 6 Variation of solar radiation with time of the day during drying of pineapples

Figure 6 shows solar radiation, it was found that solar radiation was strongly fluctuated on the first day of the experiment due to cloud. On the second, third days, solar radiation was lower than the first day because of the rain. The variation of solar radiation with time of the day during drying of pineapples varied from 138 – 749 (W/m^2).

The comparison of air temperature at three different locations inside the dryer and the ambient air temperature for the experimental runs of solar drying of pineapples are shown in Figure 7.

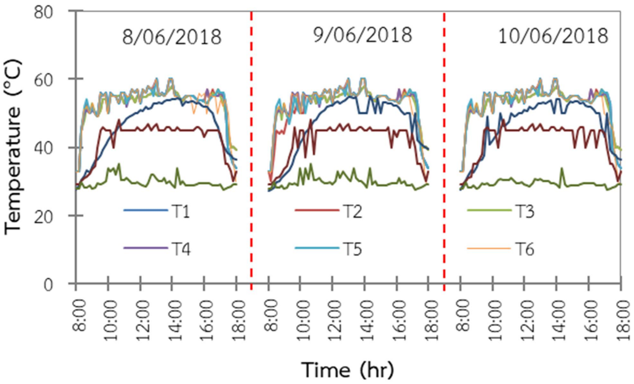

Figure 7 Variation of ambient temperature and the temperature at different positions inside the hybrid solar dryer during drying of pineapples.

The patterns of temperature change in different positions were comparable for all locations. Temperatures in different positions at these five locations varied within a narrow band. In addition, temperatures at each of the locations differed significantly from the ambient air temperature. The variation of ambient temperature and the temperature at different positions inside the hybrid solar dryer during drying of pineapples varied from 29 – 65 ($^{\circ}$C).

The relative humidity of two different locations inside the dryer and ambient air relative humidity during solar drying of pineapples are shown in Figure 8.

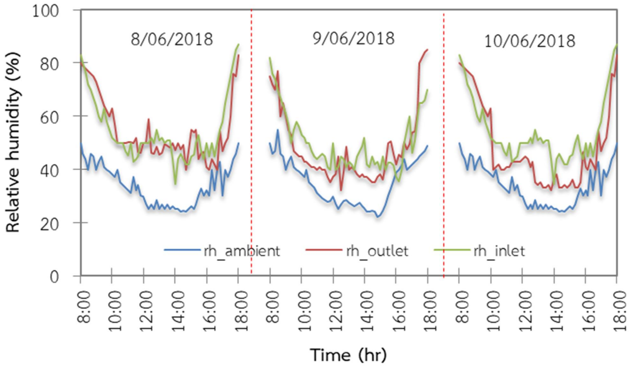

Figure 8 Variation of relative humidity with time of the day during drying of pineapples

Relative humidity decreased over time at different locations 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, there was a significant difference in relative humidity for all locations 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. Hence, the air leaving the dryer and lower relative humidity than that of the ambient air and this indicated that the exhaust air from the dryer still had drying potential for recirculation to dry the product.

The variation of relative humidity with time of the day during drying of pineapples varied from 22.0 – 85.0 (%).

The variation airflow rate with time of the day during drying of pineapples of the hybrid solar dryer are shown in Figure 9.

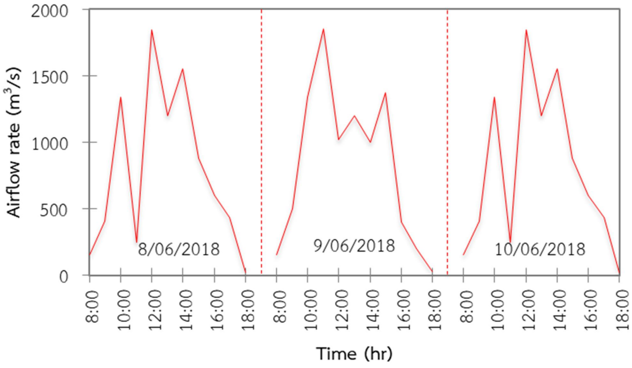

Figure 9 Variation of airflow rate with time of the day during drying of pineapples

The variation airflow rate with time of the day during drying of pineapples varied from 25 –1,800 (m^3/s).

The comparison of moisture content at three different locations inside the dryer and the open sun drying for the experimental runs of solar drying of pineapples are shown in Figure 10.

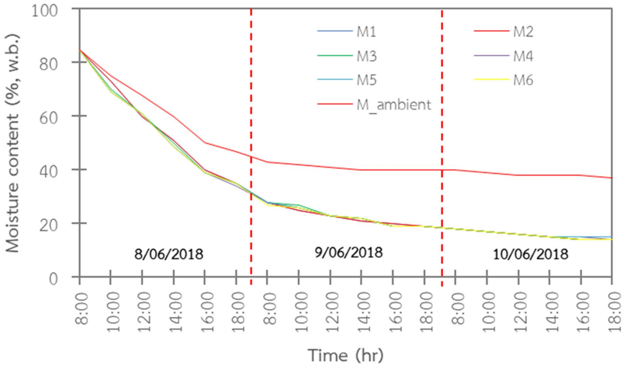

Figure 10 Comparison of the moisture contents of pineapples at different positions inside the hybrid solar dryer with those obtained by the open sun drying

The moisture content of pineapples in the hybrid solar dryer was reduced from an initial value of 83.0% (w.b.) to a final value of 10.0-13.0% (w.b.) within 3 days whereas the moisture contents of the open-sun dried samples were reduced to 39.0% (w.b.) in the same period.

2. Performance prediction by ANN model

The ANN model of the hybrid solar dryer developed for pineapple drying were trained with the experimental data from nine experiments. The data from the tenth experiment was reserved for the testing the model. After 100,000 times of iteration step of training, the square sum of difference (error) between the observed and the predicted output reached a significant low level. The comparison between the model–predicted and measured moisture contents of the dryer is shown in Figure 11.

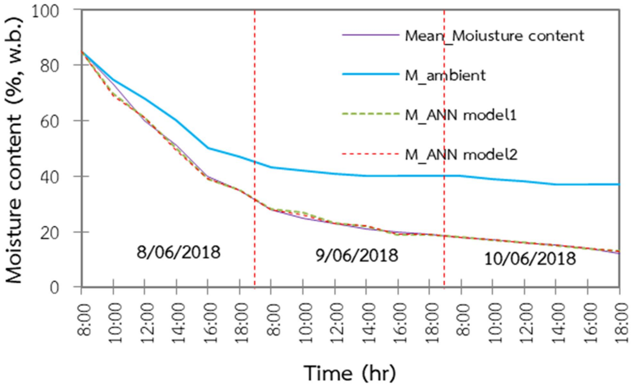

Figure 11 Predicted versus measured moisture contents of pineapples

From Figure 11, it was found that the agreement between the predicted versus measured moisture contents is good, the root mean square error (*RMSE*), and determination coefficient (R^2) of model 1 and model 2 are 0.5124, 0.9877; 0.4003, 0.9918 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 pineapples.

3. Economic Evaluation

As there are now several units of this type of dryer being used for production of dried pineapples, information used for economic evaluation is based on the field level data and recent prices of the materials used for construction of the dryers. In term of economic evaluation, the capital cost for construction and installation of the hybrid solar dryer is estimated to be USD 1,358.9 (1 USD = 31.9764 baht). Data on costs and economic parameters are shown in Table 1.

Table 1 Data on costs and economic parameters (1 USD = 31.9764 THB; 11-05-2018)

Items	Costs and Economic Parameters
Polycarbonate plates	300 USD
Solar modules and fans	150 USD
Materials of constructions	500 USD
Electricity	120 USD
Labor costs for constructions	88.9 USD
Repair and maintenance cost	1% of capital cost per year
Operating cost	200 USD per year
Price of fresh pineapples	0.156 USD kg^{-1}
Price of dried pineapples	5.0 USD kg^{-1}
Expected life of the dryer	15 years
Interest rate	1.50% (Bank of Thailand)
Inflation rate	1.46% (Bank of Thailand)

It is estimated that 1,200 kilograms of dry pineapples are produced annually. Based on these production scales, capital and operating costs, the payback period of the hybrid solar dryer for drying pineapples are estimated to be about 1 year.

Conclusions

Ten sets of full scale field level drying runs for drying of pineapples were conducted and the temperature of the drying air at the collector outlet varied from 29°C to 65°C during drying. This drier can be used to dry up to 10.0 kilograms of fresh pineapples. The pineapples dried in the hybrid solar dryer were completely protected from rain, insects and dust. The dried pineapples were a high-quality product. The performance of the hybrid solar dryer for drying pineapples has been experimentally investigated. It was found that the use of this dryer led to considerable reduction in drying time in comparison of that of open sun drying. The moisture content of pineapples in the hybrid solar dryer was reduced from an initial value of 83.0% (w.b.) to a final value of 10.0-13.0% (w.b.) within 3 days whereas the moisture contents of the open-sun dried samples were reduced to 39.0% (w.b.) in the same period, (open sun drying) final value about 10.0-13.0% (w.b.) within 5 days.

The payback period of the hybrid solar dryer for drying pineapples is estimated to be about 1 year.

An ANN model with four inputs (solar radiation, temperature, relative humidity and airflow rate), one output (moisture content) and three hidden layers were found to be able to predict the moisture content after it was adequately trained. The ANN (model 2) has a predictive power of $RMSE$ = 0.4003, R^2 = 0.9918. Within the temperature range investigated, the neural network model can be used to describe moisture content of pineapples.

Acknowledgment

The author would like to thank Program of Physics, Department of Science, Faculty of Science and Technology, Loei Rajabhat University for financial support provided for this research work. Thanks also go to Professor Dr. Serm Janjai, Department of Physics, Faculty of Science, Silapakorn University.

References

Audsley E, Wheeler J. The annual cost of machinery calculated actual cash flows, *Journal of Agricultural Engineering Research*, 1987; 23: 189-201.

Funholi A, Sopian K, Ruslan MH et al. Review of solar dryer for agricultural and marine products, *Renewable and sustainable Energy Reviews*, 2010; 14: 1-30.

Janjai S, Laksanaboonsong J, Thongsathitya A. Development of a method for generating operational solar radiation maps from satellite data for a tropical environmental, *Solar Energy*. 2005; 78: 739-751.

Janjai S, Khamvongsa V, & Bala BK. Development, design and performance of aPV- Ventilated greenhouse dryer, *International Energy Journal*. 2007; 8: 249-258.

Janjai S, Lamlert N, Intawee P, et al. Solar drying of peeled longan using a side loading type solar tunnel dryer: Experimental and simulated performance, *Drying Technology*. 2009a; 27: 595–605.

Janjai S, Lamlert N, Intawee P. et al. Experimental and simulated performance of a PV-ventilated solar greenhouse dryer for drying of peeled longan and banana, *Solar Energy*, 2009b; 83: 1550-1565.

Janjai S, Piwsaoad J, Nilnon TW. et al. Experimental performance and Neuron Network modeling of a Large-scale Greenhouse solar dryer for drying Natural rubber sheets, *Journal of Control Science and Engineering*, 2015; 1: 48-53.

Murthy MV. A review of new technologies, models and experimental investigations of solar dryers, *Renewable Energy Reviews*, 2009; 13: 835-844.

Piwsaoad J, Phusampao C. Performance of a Small-Scale Greenhouse Solar Dryer for Drying Long peppers of Ban Khokamin Community Enterprise Loei Province Thailand, *Sakon Nakhon Rajabhat University Journal of Science and Technology*, 2016; 8(2): 268-274.

Sharma A, Chem CR, Lan N.V. Solar-energy drying systems, *A review, Renewable and Sustainable Energy Reviews*, 2009; 13: 1185-1210.