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Appropriate Parameters of the ANFIS-PSO Algorithm in Determining Effective Wind Speed for Solar Dryer

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Abstract: *Solar drying is an important equipment in the cashew nut process. The important production stage of cashew nuts is the de-shell humidification of kernels in the oven drying. In this study, an adaptive neuro-fuzzy inference system (ANFIS) tuned by particle swarm optimization (PSO) has been developed to estimate effective wind speed of solar dryer. This algorithm is called the ANFIS-PSO algorithms. Six data set including temperature and humidity in the solar dryer, temperature and humidity in the solar collector, temperature and humidity of the outside environment are determined as input data. The output data is wind speed. The result show that the ANFIS-PSO model with fuzzy rule = 7 and population size = 50, gives the lowest RMSE value of 0.1691.*

Keywords: *ANFIS, Particle Swarm Optimization, Solar dryer, Solar collector*

1. Introduction

The cashew nuts products in Thailand are exported to world-wide market. The important production stage is the de-shell humidification of kernels in the oven drying. The objective of de-shelling process is to obtain the highest percentage of complete kernels and to prepare them for easy peeling [1]. Industrial drying is another method of drying, but this is more expensive. Solar drying is therefore appropriate solution because of its free availability. However, the main issue is the proper wind speed for evacuating the humidity from the solar dryer because of decreasing temperature when the wind speed is high.

In recent years, artificial intelligence methods have attracted the attention of many researchers in the field of renewable energy and forecast solar radiation [2-3]. Benmouiza and Cheknane [4] improved clustered adaptive neuro-fuzzy inference system (ANFIS) to forecast an hour-ahead solar radiation. The results show that the ANFIS with fuzzy c-means (FCM) clustering model gives the best results. However, particle swarm optimization (PSO) is commonly combined with ANFIS. Oliverira and Schirru [5] apply PSO for tuning ANFIS in sensor monitoring compared to ANFIS using one gradient descendent (GD) and genetic algorithm (GA). It found that the PSO applied in ANFIS gives the best result. Rezakazemi et al. [6] utilized of ANFIS with GA and particle swarm optimization (PSO) for evaluate of H2-selective mixed matrix membranes (MMMs). The results revealed that the ANFIS-PSO model yields better prediction in comparison to two other methods.

For this study, particle swarm optimization technique for training the antecedent parameters of an ANFIS. The proposed methodology to estimate effective wind speed of solar dryer for de-shelling stages. The results obtained from the tests are compared with similar ANFIS based on gradient descendent and particle swarm algorithm techniques for training the antecedent parameters.

2. Methodology

In order to transform raw cashew nuts into finished products, there are six stages including drying, pre-treatment, de-shelling, peeling, grading and packaging. The de-shell humidification of kernels in the oven drying is a necessary stage. This study employs particle swarm optimization algorithm by tuning a neuro-fuzzy inference system to estimate effective wind speed of solar dryer in de-shelling stages. The solar dryer system in this study composes of solar dryer, solar collector, temperature and humidity in the solar dryer, temperature and humidity in the solar collector, temperature and humidity for the outside environment, and electric fan, as shown in Figure1.

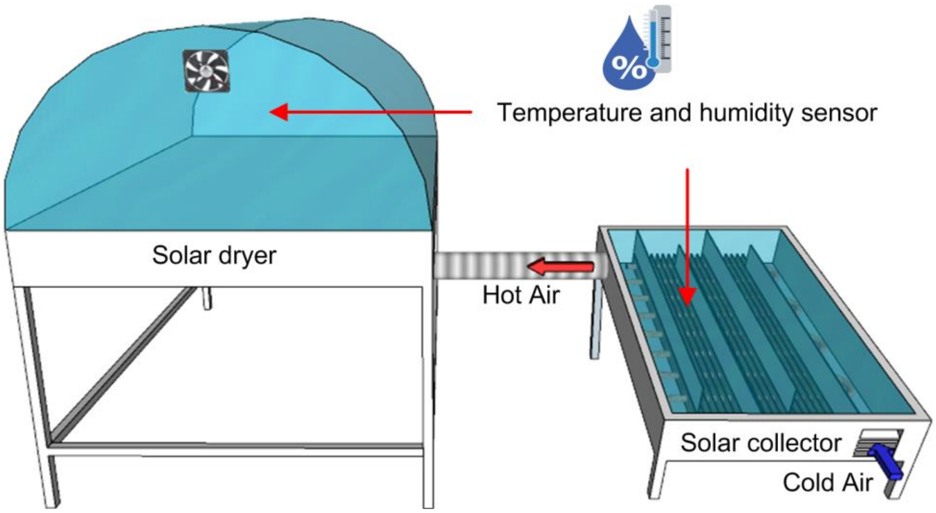

Fig. 1: The solar dryer for humidification of kernels

2.1. Data collection

Data used in this study are temperature in the solar dryer (T_s), humidity in the solar dryer (H_s), temperature in the solar collector (T_c), humidity in the solar collector (H_c), temperature of the outside environment (T) humidity of the outside environment (H) and wind speed (Sp) for five days from 10:00 to 16:00 in Uttaradit, Thailand. The set of parameters is formed as $[X]=\{T_s,H_s,T_c,H_c,T,H,Sp\}$. Optimal data criteria were selected for training and testing in accordance with equation (1). The optimal data used in this study, as shown in Table1.

$$[X]=[x_{t+1}] \qquad IF\ \ T_s^{t+1} > T_s^t \ \ AND\ \ H_s^{t+1} < H_s^t \tag{1}$$

TABLE I: The example optimal data

No.	Ts (C)	Hs (%)	Tc (C)	Hc (%)	T (C)	H (%)	Sp(m/s)
1	46.84	16.95	36.53	34.74	61.45	17.53	1.5
2	61.17	10.37	39.40	29.50	65.86	15.92	1.5
3	67.41	5.75	38.80	28.21	63.99	16.20	1.5
4	50.00	13.95	37.05	32.28	47.40	28.39	2.0
5	67.39	7.67	41.63	26.69	63.13	17.54	2.0
6	67.11	5.20	40.93	25.82	61.97	17.43	2.0
7	57.67	4.57	38.82	21.13	54.73	19.21	2.5
8	64.68	1.06	40.71	18.57	63.90	15.27	2.5
9	65.00	0.88	40.51	18.55	66.40	13.90	2.5
10	49.80	10.39	39.62	21.55	51.12	22.52	3.0
11	60.04	6.17	42.36	22.30	67.80	14.72	3.0
12	64.61	3.20	43.47	18.51	63.75	15.60	3.0
13	53.80	10.76	41.94	23.99	67.75	14.92	3.5
14	61.06	7.07	42.13	23.91	64.19	16.72	3.5
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
209	60.86	5.95	41.12	22.86	59.47	18.25	3.5

2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a hybrid machine learning technique which takes advantage from artificial neural network (ANN) and fuzzy inference system (FIS), the learning capability of ANN and human knowledge-based decision-making power of FIS. The basic architecture of ANFIS is shown in Figure2 [7]

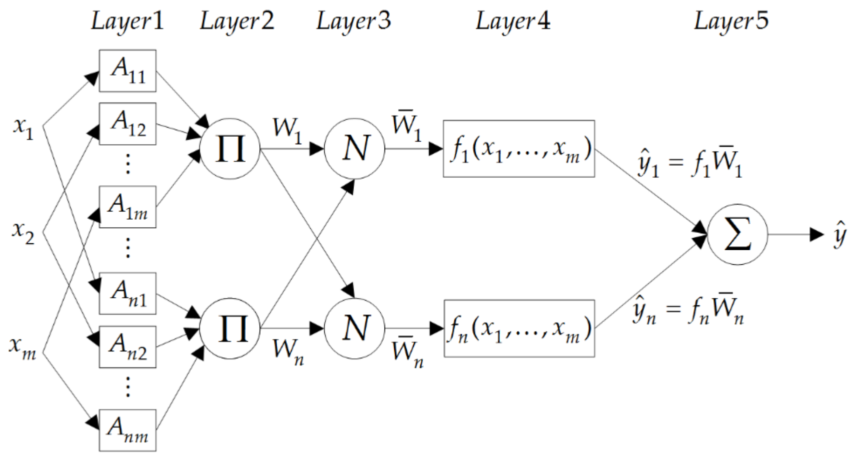

Fig. 2: An architecture of ANFIS

Form Figure2, the ANFIS in this study uses the Takagi–Sugeno–Kang model (TSK model). A typical fuzzy rule using the first-order TSK model as follow.

$$IF\ x_1\ IS\ A_{i1}\ AND\ldots AND\ x_m\ IS\ A_{im}\ THEN\ y_i\ IS\ f_i(x_1,\ldots,x_m) \tag{2}$$

Where $x_1,\ldots,x_m$ are input variables to the neuro-fuzzy inference system, $A_{i1},\ldots,A_{im}$ are antecedent membership function of each input variable for the i^{th} rule, $\hat{y}_i$ is the output of the i^{th} rule and f_i is the consequent part of TSK model. The normally five layers in ANFIS as follows [8].

- Layer 1: Adjust every node by using Equation (3):

$$O_i^1 = \mu_{ij}(x) \tag{3}$$

- Layer 2: Calculate each node by multiplying the fuzzy value, the following equation (4).

$$O_i^2 = W_i = \prod_{j=1}^{m} A_{ij}(x_i) \tag{4}$$

- Layer 3: Sum the fuzzy value of every node by equation (5).

$$O_i^3 = \bar{W}_i = \frac{W_i}{\sum_{i=1}^{n} W_i} \tag{5}$$

- Layer 4: Normalize the fuzzy value of every node, the following equation (6).

$$O_i^4 = \bar{W}_i f_i \tag{6}$$

- Layer 5: Sum all output from layer four to obtain the final output by equation (7).

$$O_i^5 = \sum_{i=1}^{n} \bar{W}_i f_i \tag{7}$$

According to, there are six factors influencing the efficiency of the solar dryer in predicting wind speed. It is input to adaptive neuro-fuzzy inference system. The input data consists of T_s, H_s, T_c, H_c, T and H. For the output from adaptive neuro-fuzzy inference system is wind speed.

2.3. The ANFIS training algorithm

2.3.1 Particle Swarm Optimization

Particle swarm optimization (PSO), invented for solving the non-linear optimization introduced by Kennedy and Eberhart [9], is based on the concept of the foraging of bird flock behavior to find the optimized solution area. The PSO algorithm includes a collection of particles which move within the research space. Each particle keeps their best position value, which can be demonstrated by equation (8) and Equation (9).

$$P_{best,i}^{t+1} = \begin{cases} P_{best,i}^{t+1} & if \;\; f(x_t^{t+1}) > P_{best,i}^{t} \\ x_i^{t+1} & if \;\; f(x_t^{t+1}) \leq P_{best,i}^{t} \end{cases} \tag{8}$$

$$G_{best} = \min\left\{P_{best,i}^{t+1}\right\}, \; where \; i \in \left[1,...,n\right] \; and \; n > 1 \tag{9}$$

Where $P_{best,i}$ is the best position that the individual particle, G_{best} is the best position discovered by any of the particles in the entire swarm. In this method, each individual particle, $i \in \left[1,...,n\right]$, where $n > 1$, has been calculated in the search space x_i . The new velocity is calculated as in equation (10).

$$v_{ij}^{t+1} = \omega v_{ij}^{t} + c_1 r_{1j}^{t}[P_{best,i}^{t} - x_{ij}^{t}] + c_2 r_{2j}^{t}[G_{best} - x_{ij}^{t}] \tag{10}$$

Where v_{ij}^{t} is the velocity of the particle i in the dimension j of time t, ω is an inertia weight, x_{ij}^{t} is a position, $P_{best,i}^{t}$ is the best position of a particle of time t, G_{best} is the best position of the whole particle system, c_1 and c_2 are the constant accelerations in searching, and r_{1j}^{t} and r_{2j}^{t} are the random numbers between 0 and 1 at time t.

2.4. The Experimental Setting

For ANFIS and PSO, there are no theoretical existing criteria to notify what the best parameter values are [10]. According to previous study [11] [6], the parameters setting for ANFIS and ANFIS-PSO algorithms are determined as in Table 2.

TABLE II: The Arrangement of Channels

Specification	Proposed ANFIS models	
	ANFIS	ANFIS-PSO
Iteration	500	500
Fuzzy type	Sugeno	Sugeno
Input/outputs	6/1	6/1
Input MF Type	Gaussian	Gaussian
Output MF Type	Linear	Linear
Fuzzy rules	5,7,9	5,7,9
Population size	-	10,20,30,40,50
Inertia weight	-	1.0
Damping ratio	-	0.99
Personal learning coefficient	-	1.0
Global learning coefficient	-	2.0

3. Result and Discussion

In this section, the prediction results from different proposed models in predicting the wind speed of solar dryer for de-shelling stages are presented. The root mean square error (RMSE) and correlation coefficient (R) are applied to evaluate the superiority of the model generated by ANFIS and ANFIS-PSO

3.1. The Optimal Parameter of ANFIS and ANFIS-PSO

The optimum setting can enhance the reliability of the model. The different values of fuzzy rules and population sizes are investigated. For train data, the performance values of ANFIS, RMSE = 0.36786 and R = 0.87941. For test data, RMSE = 0.37132and R = 0.88072, as shown in Figure 3.

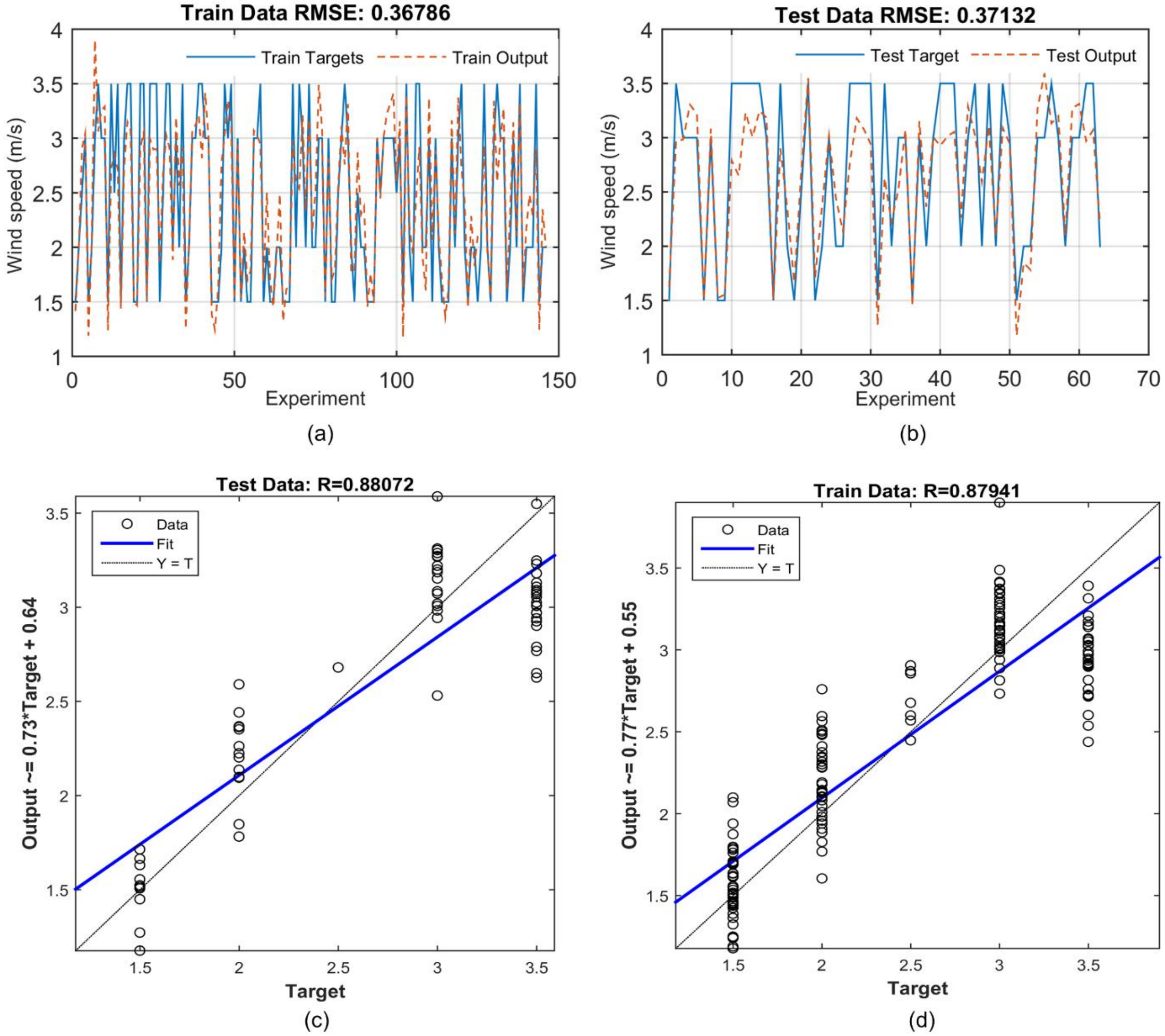

Fig. 3: The performance results of ANFIS model.

TABLE III: The Optimal parameters of ANFIS-PSO.

Fuzzy rules	Population size	Train Data		Test Data	
		RMSE	R	RMSE	R
5	10	0.21452	0.9625	0.20344	0.96515
	20	0.17768	0.974	0.15321	0.97955
	30	0.18327	0.97191	0.21101	0.96192
	40	0.17335	0.9754	0.18603	0.97058
	50	0.21889	0.95913	0.18144	0.97133
7	10	0.22055	0.96032	0.18417	0.97321
	20	0.18205	0.97251	0.18669	0.97209
	30	0.19658	0.969	0.17936	0.97306
	40	0.23754	0.95158	0.19479	0.96685
	50	0.16908	0.9765	0.14423	0.98254
9	10	0.21763	0.96139	0.22045	0.96116
	20	0.17444	0.97574	0.17409	0.97632
	30	0.19244	0.96943	0.21916	0.96078
	40	0.16668	0.97671	0.1955	0.96886
	50	0.16876	0.9768	0.2185	0.9224

As seen in Table 3, the optimal parameters of ANFIS-PSO algorithm are the case of 500 iterations with fuzzy rule = 7 and Population size = 50. For train data, the performance values of ANFIS-PSO, RMSE = 0.16908 and R = 0.9765. For test data, RMSE = 0.14423 and R = 0.98254, as shown in Figure 4.

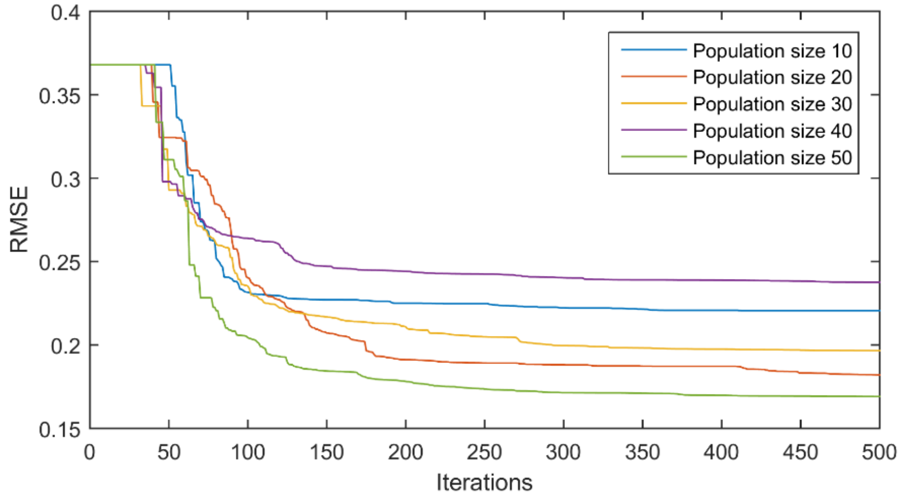

Fig. 4: The optimal parameters of ANFIS-PSO with 500 iterations and fuzzy rule is 7.

4. Conclusion

In this study, the particle swarm optimization is applied for tuning a neuro-fuzzy inference system to estimate effective wind speed of solar dryer in de-shelling stages. Temperature and humidity in the solar dryer, temperature and humidity in the solar collector, temperature and humidity of the outside environment are collected as input data. The wind speed is used as output data. The data cover five days period from 10:00 to 16:00 in Uttaradit, Thailand. To verify the proposed model, ANFIS and ANFIS-PSO are compared. In the case of fuzzy rule = 7 and population size =50, the ANFIS-PSO model provides the lowest RMSE value of 0.1691. For future study, the optimal parameter values of ANFIS-PSO should be applied in controller to estimate effective wind speed for solar dryer.

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