Development and evaluation of an adaptive neuro-fuzzy interface models to predict performance of a solar dryer

Nikrooz Bagheri[1*], NazillaTarabi[2], HosseinJavadikia[3]

(1. *Assistant professor of Agricultural Engineering Research Institute, AREEO, Iran;*
2. *Former MS.c Student in Mechanics of Agricultural Machinery, University of Tehran,Iran;*
3. *Assistant professor in Mechanical Engineering of Agricultural Machinery, Razi University of Kermanshah, Iran.*)

Abstract: This research is carried out to predict energy efficiency of a solar dryer by adaptive neuro-fuzzy inference system (ANFIS) model. In this model, temperatures in the collector inlet, collector outlet and in the dry chamber exit and also absorbed heat energy by collector and necessary energy for evaporation of product moisture were considered as an ANFIS network inputs. To investigate the capability of ANFIS models in prediction of dryer efficiency, empirical model was used and its result was compared by ANFIS models. To evaluate an accuracy of ANFIS models, statistical parameters, namely, mean absolute error, mean squared error, sum squared error, correlation coefficient (R) and probability (P) were calculated. Results indicated that coefficient of determination for ANFIS models were in comparison with empirical models whereas amounts of SSE and MSE were lower. From the results of this research, it is concluded that ANFIS models could be efficient in predicting the energy efficiency of a forced-convection solar dryer.

Keywords: solar drying, energy efficiency, ANFIS, empirical modelling

Citation: Bagheri, N., H. Javadikia, and N. Tarabi. 2015. Development and evaluation of an adaptive neuro-fuzzy interface models to predict performance of a solar dryer. Agric Eng Int: CIGR Journal, 17(2):112-121.

1 Introduction

Because the importance of energy consumption amount in performance evaluation of dries, investigation of energy efficiency in dryers has been carried out by different researchers (Arjona et al.,2005; Othman et al., 2006; Bagheri et al.,2011). Many researchers have used the exponential drying model to describe drying behavior of agricultural products (Inciand Pehlivan, 2004; Simalet al., 2005). In the past, researchers have solved analytically several inter-dependent quasi-steady state energy balance equation for performance prediction of solar dryers(Goyal and Tiweri, 1999).However, such models are not widely used because of their complexity and long computing time required for their solution (TripathyandSubodh, 2009).Empirical models usually give very accurate results for each specific experiment but the equation is not valid for other conditions and there is no way to obtain a general equation for a wide range of drying parameters. This problem may be avoided by the use of analytical drying models but these models are generally solutions of simultaneous heat and mass transfer differential equations and the final result may be very complicated and difficult to use in actual drying systems (Sogi et al., 2003).However, Fuzzy logic (FL) offers the mathematical framework for dryers (Kiralakis and Tsourveloudis, 2005)and also artificial neural network (ANN) can solve the problem with a reasonable accuracy. So, adaptive neuro-fuzzy inference system (ANFIS) as a combination of ANN and fuzzy systems and a beneficial method is used to integrate the best features of Fuzzy logic System and Neural Network and this method can solve non-linear problems (Serge, 2001; Buragohain and Mahanta, 2008; Metinand Murat, 2008). This technique is particularly useful for engineering applications where classical approaches fail or they are too complicated (Cheng et al., 2002). The ANFIS method

Received date: 2014-07-14 **Accepted date:** 2015-04-13
***Corresponding author: NikroozBagheri,** Assistant Professor of Agricultural Engineering Research Institute, AREEO, Iran. Email: n.bagheri@areo.ir

is ideal for interpretation of non-linear systems, like soil–plant–air systems (Arkhipov et al., 2008).

Recently, ANN models have also been used to describe drying behavior of different agricultural products such as carrot (Erenturk and Erenturk, 2007; Kerr et al., 2006), ginseng (Martynenko and Yang, 2006), cassava and mango (Hernandez-Perez et al.,2004) and echinaceaangustifolia (Erenturk et al 2004). Farkas et al (2004) studied ten different NN topologies to model grain drying. Inlet and outlet air temperatures, absolute humidity and air flow were considered as the input variable. The results showed that moisture distribution in the drying bed could be well modelled using a neural network (Farkas et al.,2004).Satish and Pydisettee (2005) used ANN for modelling the performance of a continuous fluidized bed dryer. It was found that ANN model fit the experimental data model with low percentage error(Satishand Pydisettee, 2005). Movagharnejad and Nikzad (2007) modelled drying of tomatoes in a tray dryer covering different variables such as heater power and air flow velocity. The data were modelled using ANN and empirical mathematical equations. It was found that the predictions of ANN model fit the experimental data more accurately in comparison with the various mathematical equations (Movagharnejad and Nikzad, 2007).Chegini et al (2008) studied the effects of feed flow rate, inlet-air temperature, and atomizer speed, in an orange juice semi-industrial spray dryer. A supervised ANN was developed to predict seven performance indices based on the three input variables. The results confirmed that the ANN model was able to produce simultaneously seven outputs(Chegini et al., 2008).Mousavi and Javan (2009) used ANN and Neuro-Taguchi's method to model and simulate apple drying. The results demonstrated that the use of Neuro-Taguchi's method could give some improvements over neural network accuracy as compared with conventional neural networks approach (Mousavi and Javan, 2009). Mansor et al (2010) designed a fuzzy logic controller for grain drying in order to obtain the grain output moisture content close to the set-point in spite of disturbance. The overall results of the experiments were indicated that the fuzzy logic controller was stable and robust towards input disturbance (Mansor et al., 2010).Menlik et al (2010)used an ANN model to determine drying behaviour of apples in the freeze-drying process. This study confirmed the ability of the developed model to determine and predict the drying behaviour of apples (Menlik et al., 2010). Abakarov et al (2012) developed a fuzzy logic-based control system for a solar dryer. Findings from this study would suggest that the developed fuzzy logic-based control system is able to tackle difficulties related to the control of solar drying process (Abakarov et al., 2012).

Totally, optimization of solar dryer systems is used to reduce system total cost, increase life cycle savings and improve thermal efficiency (Sharma and Siddhartha, 2012). So, based on the importance of energy efficiency in dryers and capabilities of ANFIS in prediction, the main objective of this research is to develop and evaluate an ANFIS model to predict energy efficiency of a forced-convection solar dryer.

2 Materials and Methods

2.1 Experimental procedures

The experimental solar dryer is designed and constructed for drying leafy vegetables (Figure1). In this pilot dryer, hot air was provided by forced convection through an air solar collector. Two main parts of the dryer were fined-flat collector and dryer chamber. The area of the collector was 1.83 m^2 and the dryer chamber had an axial tube fan and two sliding trays with total area of 1 m^2. An axial tube fan with 12 cm diameter, 210 m^3/h flow, 2300 r/min, 38 W was used (Bagheri et al., 2011).To measure temperature, temperature sensors (SMT 160-30) were installed in the collector inlet (T_1 as ambient temperature), collector outlet (T_2) and in the dry chamber exit (T_3). Because of long distances among the collector input, the collector output and the air exit from the dryer chamber where temperatures should be determined, digital temperature sensors were used. These sensors guarantee data transferring with high accuracy and minimum error due to long wires connected to the sensors. A monitoring system was constructed for recording sensors data and calculating the current dryer efficiency.

All experiments were carried out in three replications from 9 Am to 5 Pm in July with average ambient temperature of 39 ℃ during the experimental hours, total daily solar radiation of 26.288 MJ/m^2 and the monthly average of air relative humidity of 39%. In each replication, 5 kg of mint (with initial moisture content of 80%) was dried in the dryer.

Figure 1The experimental solar dryer

2.2Calculation of solar dryer energy efficiency

To calculate energy efficiency of a convective solar dryer, Equation 1 is used (Augustus Leon et al., 2002):

$$E = \frac{M_w.L}{I_t.A_c + E_f} \quad (1)$$

E: current dryer efficiency, decimal

M_w: evaporated moisture mass of the product, kg

L: specific latent heat of water vaporization, kJ/kg

I_t: solar radiation energy per collecting area, kJ/m^2

A_C: collector area, m^2

E_f: fan electric energy, kJ

The quantity of solar radiation energy in collector area is equal to the absorbed heat energy in it (DuffieandBeckman, 1991) (Equation 2):

To link the user to the monitoring system, an ActiveX control was programmed and installed on the computer being executable in Visual Basic 6.0. Using “Mscomm” control, receiving and sending information from/to RS232 port become possible.

$$\sum I_t.A_c = \sum \frac{Q_{in}}{E_c} \quad (2)$$

$I_t. A_c$:total solar radiation energy in collector area,kJ

Q_{in}:absorbed heat energy by collector, kJ

E_c: collector efficiency. 40% for this solar drier

Based on energy balance Equation 3 (SoheiliMehdizadeh et al., 2006):

$$Q_{in} = M.C_p(T_2 - T_1) \quad 3)$$

M: air mass (mixed of dry and wet air),kg

C_p: air specific heat, at 1 atmosphere pressure, 1.006kJ/kg. K

T_2: air temperature at the collector exit, K

T_1: air temperature at the collector inlet, K

Based on energy balance equation, the necessary energy for evaporation of product moisture is equal to (Equation 4):

$$M_w.L = M.C_p(T_2 - T_3) \quad (4)$$

T_3: air temperature at the dryer chamber exit, K

So, fan electric energy is (Morey & Gustafson, 1978) as Equation 5:

$$E_f = \frac{P_w.t}{E_E.E_m} \qquad (5)$$

P_w: power of fan outlet air, W

t: time, s

E_E: electromotor electric efficiency, %

E_m: impeller mechanical efficiency, %

The power of outlet air from fan (Bleier, 1998) is as Equation 6:

$$P_w = 9.81Q.Tp \qquad (6)$$

Tp: total pressure, mm WC

Q:air flow, m^3/s

2.3Modelling energy efficiency by empirical models

To model energy efficiency by empirical models (E), Design Expert Software version 7 by Response Surface Method (RSM) is used. Four linear models with different inputs, namely, E_1 (T_1 and T_2 as inputs), E_2 (T_1 and T_3 as inputs), E_3 (T_2 and T_3 as inputs) and E_4 (Q_{in} and Q_{out} as inputs) were extracted and Analysis of Variance (ANOVA) for all empirical models was carried out. So, correlation between predicted values by RSM and experimental values was obtained. Finally, the result of this model was compared with ANFIS model.

2.4Modelling energy efficiency by ANFIS models

4 ANFIS models with different variables as input variable were used to model energy efficiency of the solar drier. These models were A_1 model (T_1 and T_2 were considered as input variables); A_2model (T_1 and T_3 were considered as input variables); A_3model (T_2 and T_3 were used as input variables) and finally A_4model (Q_{in} and Q_{out} were considered as input variables).For all ANFIS models, 30 percent of data sets were used to test the models and check the ability of generalization the model.

In order to create FIS using ANFIS, fuzzy logic toolbox of MATLAB, version 7.10.0.499 was used.The structure of generated A1 (Figure2) is composed of a rule-based system with three components: membership functions of input-output variables, fuzzy rules, and output characteristics and system results (Krueger et al.,2011).Overall, five important adjustments were made in the structure of ANFIS network. These settings include type of membership function input, number of membership function input, type of membership function output (constant or linear), type of optimization method and number of epochs. In order to determine the optimal number of epochs, the error for the validation data set was obtained. Fuzzy rules of A1 model obtained by artificial neural network are shown in Figure 3. These rules consist of nine rules between T_1 and T_2 as input variables and E_1 as output variable in "If -Then" format.

To author: please place Figure 2 and Figure 3 at this place.

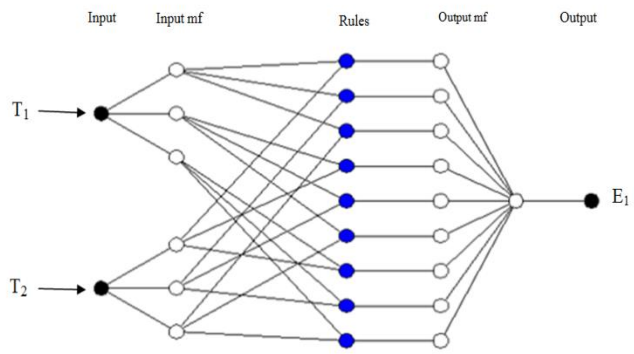


Figure 2 Structure of generated A1 mode

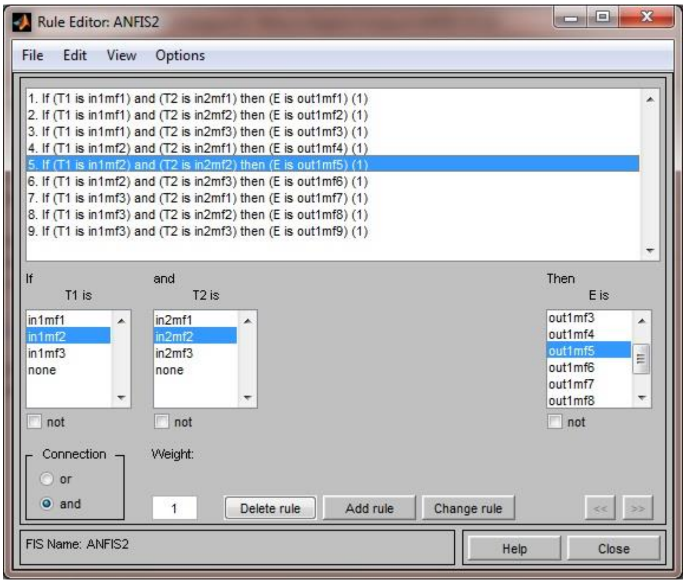


Figure 3Fuzzy rules of A1 model

To obtain the best model, some statistical parameters, namely, Sum Square Error(SSE), Mean Absolute Error (MAE), Mean Square Error (MSE), P and R were calculated for 4 ANFIS models.

3 Results and Discussion

3.1 The results of modelling energy efficiency by empirical models

The result of Analysis of Variance (ANOVA) for energy efficiency empirical models (E_1 to E_4)is shown in Table1.

Table 1Analysis of variance (ANOVA) energy efficiency empirical models

Output	Inputs	Model	C.V %	MSE	SSE	R^2	PRESS
E_1	$\frac{T_1{}^{*}{}_{(0.026)}\ (^oK)}{T_{2(0.024)}\ (^oK)}$	Linear	45.94	4.11e-4	4.93e-3	0.27	4.78**
E_2	$\frac{T_{1\ (0.22)}\ (^oK)}{T_{3\ (-0.26)}\ (^oK)}$	Linear	33.45	1.67e-3	0.02	0.61	2.54
E_3	$\frac{T_{2\ (0.25)}\ (^oK)}{T_{3\ (-0.32)}\ (^oK)}$	Linear	32.82	1.93e-4	3.47e-3	0.62	2.47
E_4	$\frac{Q_{in(0.31)}\ (kJ)}{Q_{out(-0.30)}\ (kJ)}$	Linear	30.06	3.59e-8	5.13e-9	0.68	2.07

Note : * Values in parentheses: standard errors of parameter ($P<0.05$)

**The Predicted Residual Sum of Squares (PRESS) shows how well the model fits each point in the design. The smaller the PRESS value, the better the model fits the data points.

Based on ANOVA results, E_4 model with using Q_{in} and Q_{out} as input variables had higher coefficient of determination ($R^2$of 0.68) and lower amount of MSE (3.59e-8) in comparison with other empirical models. It is indicated that Q_{in} and $Q_{out}$are good input variables for prediction of energy efficiency. The second modelfor presenting energy efficiency was E_3 with usingT_2 and T_3 as input variables. The results indicated that using T_2 and T_3 or T_1 and T_3 as input variables have similar results because $R^2$and MSEvaluesfor these two models were very closed to each other (R^2 of 0.62 and 0.61 for E_3 and E_2, respectively; MSE of 1.93e-4 and 1.967e-3 for E3 and E_2,respectively).Also, results showed that coefficient of determination for empirical models were low when the input variables were T_1 and T_2. Comparison of predicted energy efficiency by empirical models and experimental data are indicated in Figure4. This figure shows that the correlation of predicted values by experimental ones is higher for E_4 in comparison with other empirical models.

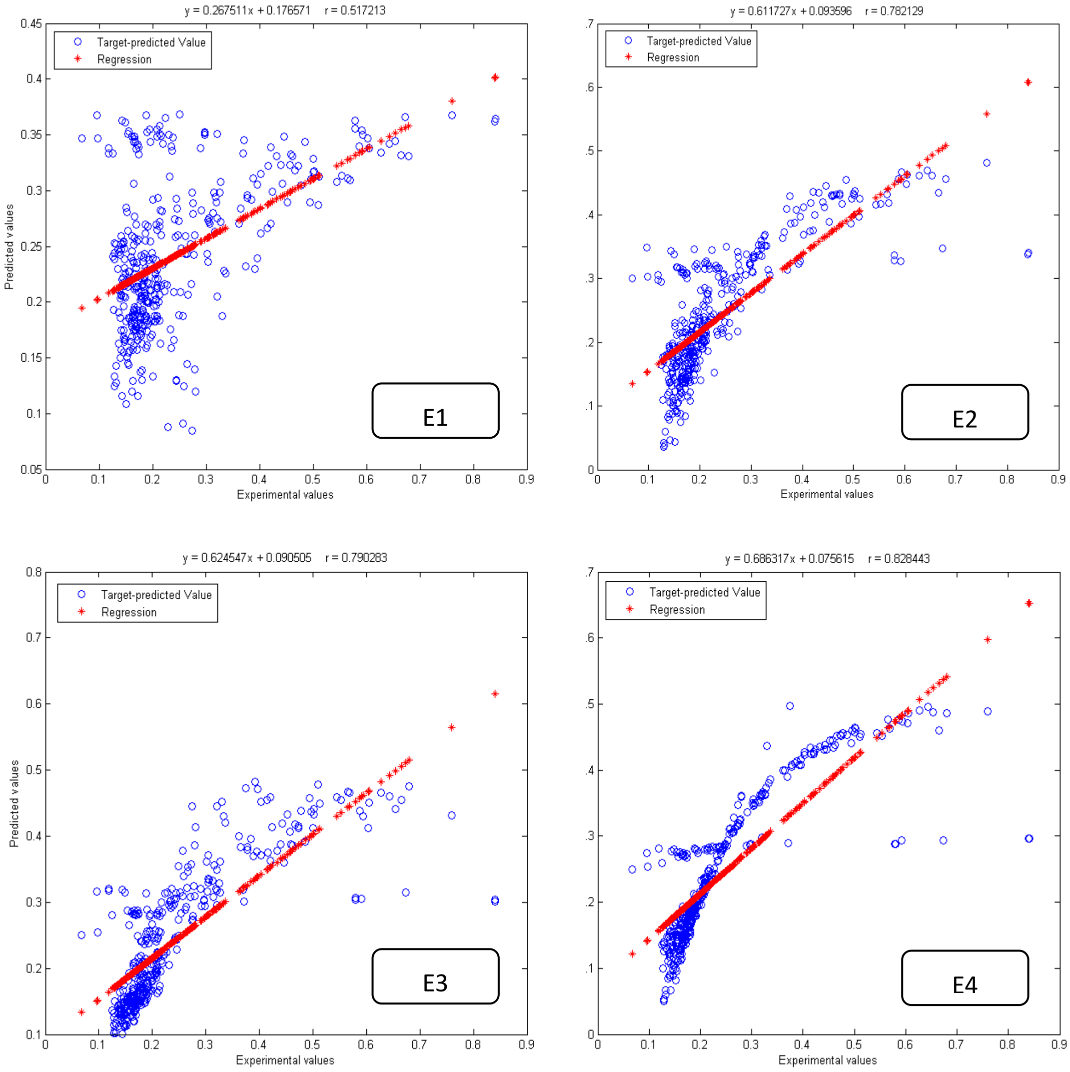
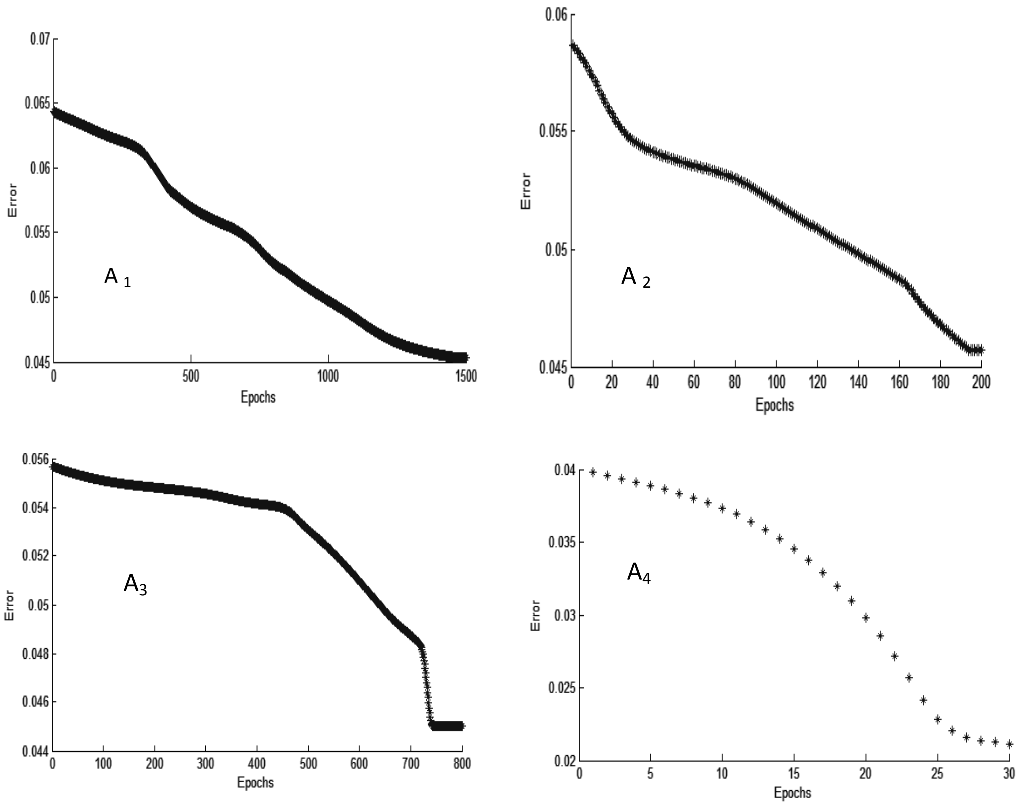


Figure4 Comparison of experimental and predicted values by empirical models

3.2 The results of modelling energy efficiency by ANFIS models

Figure5 shows the effect of epoch number changes on error value for 4 ANFIS (A_1 to A_4) models. Results indicated that for all models, error decreased by increasing number of epochs. For A_3 model, with increasing number of epochs from 0 to 400, error value didn't have considerable changes. For A_1, A_2, A_3 and A_4, number of necessary epochs for minimization of error were 1500, 200, 800 and 30, respectively. For these epochs, error was about 0.04.



Features of ANFIS models with different input variables for prediction of energy efficiency in the solar dryer are presented in Table2. As it is shown in this table, the correlation coefficient (R) for A_1, A_2, A_3 and A_4 obtained 0.936, 0.935, 0.936and 0.986, respectively which shows that $A_4$by having Q_{in} and Q_{out} as input variables had lower amount of SSE, MSE and MAE in comparison with other 3 ANFIS models. So, A_3 and A_2had similar R value. Whereas A_3 had minimum error after 800 epochs but for A_2error was minimum after 200 epochs. Close to zero values for MSE indicate that there are no differences between the predicted and measured data for ANFIS models.

Table2Features of ANFIS models with different input variables for prediction of energy efficiency

No	Inputs	Number of mf input	Type of mf input	Type of mf output	Type of optimization method	Number of Epochs	MSE	MAE	SSE	R
A_1	T_1 T_2	3	Generalized bell	Linear	Hybrid	1500	0.002	0.031	0.79	0.94
A_2	T_1 T_3	3	Gaussian2	Linear	Hybrid	200	0.002	0.023	0.80	0.93
A_3	T_2 T_3	3	Gaussian	Linear	Hybrid	800	0.002	0.023	0.78	0.94
A_4	Q_{in} Q_{out}	3	Gaussian	Linear	Hybrid	30	0.0004	0.007	0.17	0.99

As, it is shown in Table 1 and Table 2, R value for empirical models (E_1 to E_4) were 0.51, 0.78, 0.78 and 0.82 and for the ANFIS models (A_1 to A_4) were 0.94, 0.93, 0.94 and 0.99, respectively.

Predicted data versus the same set of measured data for ANFIS models ($A_1$to A_4) is depicted in Figure6. Results showed that the relationship between predicted and experimental data was closed to linear relationship for all models. So, the scatter plots showed that the predictive capability was satisfactory and data points were well concentrated around the ideal unity-slope line selected. For all data, the linear adjustment between measured and estimated values gives almost a slope practically equal to 1.Therefore, there was good match between the predicted and experimental values in all ANFIS models, especially for A_4 that had maximum regression in comparison with other models. As, A_4model presents energy efficiency based on Q_{in} and Q_{out} as input variables so, in can be concluded that Q_{in} and Q_{out} are good factors for prediction of energy efficiency of ANFIS models in comparison with Temperature based models (T_1-T_2 and T_3). Thus, this model could be used to determine the energy efficiency of the forced convection solar dryer.

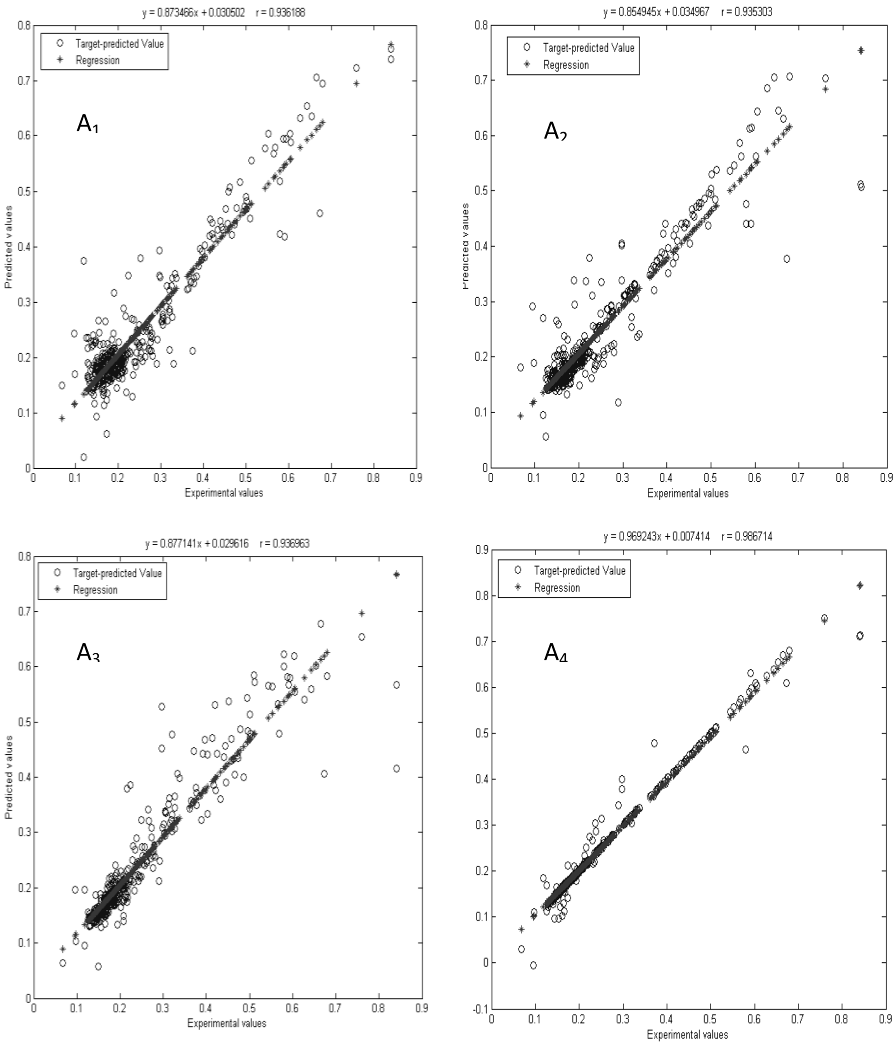


Figure6 Comparison of experimental and predicted data by ANFIS models

Comparing the results of ANFIS models by empirical models shows that the predicted data by ANFIS models was more correlated by experimental data. So, the developed ANFIS network has a good performance in predicting energy efficiency of the solar drier.

For both ANFIS and empirical models, mathematical equations by using Q_{out} and Q_{in}as input variables indicated higher correlation and lower error whereas equations by having T_1, T_2 and T_3as input variables had lower correlation by experimental data. As Q_{in} and Q_{out} beside depending on T are dependent to some other drying factors, namely, air mass, air specific heat, evaporated moisture mass of the product and specific latent heat of water vaporization, so, they can consider more effective variables on dryer energy efficiency and finally, they can model and predict energy efficiency of the solar dryer more accurately.

4 Conclusions

The present research is carried out to develop an ANFIS model to predict and evaluate the energy efficiency of a forced-convection solar dryer. Considering the results obtained from this research, the following conclusions can be drawn:

- The correlation coefficient between experimental data and empirical models (E_1 to E_4) were 0.51, 0.78, 0.78 and 0.82, respectively.
- The correlation coefficient between experimental data and ANFIS models (A_1 to A_4)modelswere 0.936, 0.935, 0.936 and 0.986, respectively.
- Based on the error analysis results, it was found that the ANFIS model was more appropriate configuration for prediction of energy efficiency in comparison with empirical model.
- Between ANFIS and empirical models, A_4 and E_4 models by having Q_{in} and Q_{out} as input variables had lower amount of error in comparison with other models which indicates that Q_{in} and Q_{out} are good input variables for prediction of energy efficiency in comparison with T based models.

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