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Comparison of Thermal Performances Predicted and Experimental of Solar Air Collector

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Abstract: In this study, thermal performance of solar air collector system which was experimentally constructed was obtained for different operating conditions. Experiments were conducted under Turkey/Mersin climatic conditions. Then, Neural Network (NN) models have been developed for the prediction the thermal performance of solar air collectors. Experimental data were used for training and testing of the networks. The inputs of the network are inlet and outlet air temperature to collector, solar radiation and air mass flow rate and the output is thermal performance of solar air collector. Using the weights obtained from the trained network a new formulation is presented for the calculation of the performance; the use of NN is proliferating with high speed in simulation. The R^2-values obtained when unknown data were used to the networks was 0.9985 which is very satisfactory. The use of this new formulation, which can be employed with any programming language or spreadsheet program for the estimation of the thermal performance of solar air collectors, as described in this paper, may make the use of dedicated NN software unnecessary.

Key words: Solar air collector, neural networks, thermal performance, solar energy, experimental analysis, performance prediction

INTRODUCTION

Turkey has an important potential for renewable energy sources, especially solar energy. Solar energy can be used in the various applications (heating, cooling, drying and power generation). The major component of any solar energy system is the solar collector. Solar collectors are special kind of heat exchangers that transform solar radiation energy to internal energy of the transport medium. This is a device which absorbs the incoming solar radiation, converts it into heat and transfers this heat to a fluid (usually air, water, or oil) flowing through the collector. The solar energy thus collected is carried from the circulating fluid either directly to the hot water or space conditioning equipment (Duffie and Beckman, 1991; Kalogirou, 2004a,b).

The air collector is used for heating air in drying agricultural products and as an air heater in combination with auxiliary heaters for air conditioning of buildings (Karsli, 2007; Mittal and Varshney, 2006; Koyuncu, 2006; Hegazy, 2000; Karim and Hawlader, 2004). Solar air collector converts sunlight into heat extracted from the collector by moving fluid. The useful thermal energy delivered by the heater can be used for different applications.

Thermal performance of the solar air collectors depends on the material, shape, dimension and layout of the collector. Thermal performance is low because of low thermal capacity of air and low heat transfer coefficient between the absorber plate and air. Performance improvement can be achieved using diverse materials, various shapes and different dimensions and layouts. The modifications to improve the heat transfer coefficient between the absorber plate and air include the use of an absorber with fins attached, corrugated absorber, matrix type absorber, with packed bed, with baffles and different configurations are given in the literature (Kolb *et al*., 1999; Esen, 2007; Karim and Hawlader, 2006; Ucar and Inallı, 2006).

In this study, the thermal performance of solar air collector with corrugated absorber plate was experimentally investigated. Then, Neural Network (NN) models have been developed for the prediction the thermal performance of solar air collectors. The thermal performance of collector which is obtained experimentally has been compared with thermal performance of collector which is obtained from NN. In addition, in order to calculate thermal performance of solar air collector, a new formulation was derived.

THEORETICAL ANALYSIS OF AIR COLLECTOR

The efficiency of solar collectors is the ratio of useful energy obtained in collector to solar radiation incoming to

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collector. It can be formulated as the following (Duffie and Beckman, 1991; Ucar and Inallı, 2006)

$$\eta = Q_u/A_cI \tag{1}$$

The useful energy transferred to fluid is:

$$Q_u = A_cF_R[(\tau\alpha)I\text{-}U_L(T_f\text{-}T_a)] \tag{2}$$

The collector heat removal factor (F_R) is the ratio of useful heat obtained in collector to total heat collected by collector when the absorber surface temperature is equal to fluid entire temperature on every point of the collector surface.

$$F_R = \frac{\dot{m}c_p}{A_cU_L}\left[1 - e^{-(A_cU_LF')/(\dot{m}c_p)}\right] \tag{3}$$

The collector overall heat loss coefficient (U_L) is the sum of top, bottom and edge heat loss coefficients and can be written:

$$U_L = U_t + U_b + U_e \tag{4}$$

The top heat loss coefficient (U_t):

$$U_t = \left\{\frac{N}{\frac{C}{T_{p,m}}\left[\frac{T_{p,m}-T_a}{N+f}\right]^e} + \frac{1}{h_w}\right\}^{-1} + \frac{\sigma\left(T_{p,m}+T_a\right)\left(T_{p,m}^{\ 2}+T_a^{\ 2}\right)}{\frac{1}{(\varepsilon_p + 0.00591Nh_w)} + \frac{2N+f-1+0.133\varepsilon_p}{\varepsilon_g} - N} \tag{5}$$

Where:

$$C = 520(1\text{-}0.000051\beta2)(0° < \beta < 7O°) \tag{6}$$

$$f = \left(1+0.089h_w - 0.1166\,h_w\varepsilon_p\right)\left(1+0.07866N\right) \tag{7}$$

$$h_w = 5.7+3.8V \tag{8}$$

$$e = 0.43\left(1 - \frac{100}{T_{p,m}}\right) \tag{9}$$

N = No. of glass covers.

The bottom heat loss coefficient (U_b):

$$U_b = \frac{k}{L} \tag{10}$$

The edge heat loss coefficient (U_e):

$$U_e = \frac{(UA)_e}{A_c} \tag{11}$$

$$(UA)_e = \frac{h_s}{L_s}PL_c \tag{12}$$

The collector efficiency factor (F') can be written:

$$F' = \frac{h_rh_1 + h_2U_t + h_2h_r + h_1h_2}{\left(U_t + h_r + h_1\right)\left(U_b + h_2 + h_r\right) - h_r^{\ 2}} \tag{13}$$

Where:

$$h_r = \frac{\sigma\left(T_1^{\ 2} + T_2^{\ 2}\right)\left(T_1 + T_2\right)}{\frac{1}{\varepsilon_g} + \frac{1}{\varepsilon_p} - 1} \tag{14}$$

The Nusselt number is needed for calculation of h_1 and h_2 heat transfer coefficients in the air channel of solar collector. The Nusselt numbers can be used as the following equation for various Reynolds numbers (Ucar and Inallı, 2006)

$$100<Re<2100 \quad Nu = 0.344\ Re^{0.35} \tag{15}$$

$$2100<Re<2850 \quad Nu = 16810^{-9}\ Re^{2.25} \tag{16}$$

$$2850<Re<5650 \quad Nu = 2.5510^{-3}\ Re^{1.04} \tag{17}$$

$$5650<Re<100000 \quad Nu = 19.810^{-3}\ Re^{0.8} \tag{18}$$

MATERIALS AND METHODS

The experimental setup of solar air collector is shown in Fig. 1. The collector has L_c = 1.8 m length and W_c = 0.8 m width. Experimental measurements were done on days 18-31 May of 2005 (Özdemir, 2005). Solar air collector was positioned towards the south at an angle of 36° which was optimum for this month in Mersin-Turkey (36.48° latitude and 34.38° longitude). The detailed configuration of corrugated plate is shown in Fig. 2. The detailed specifications of the collector are shown in Table 1.

The measured variables in the experiment include inlet and outlet air temperatures, ambient temperature,

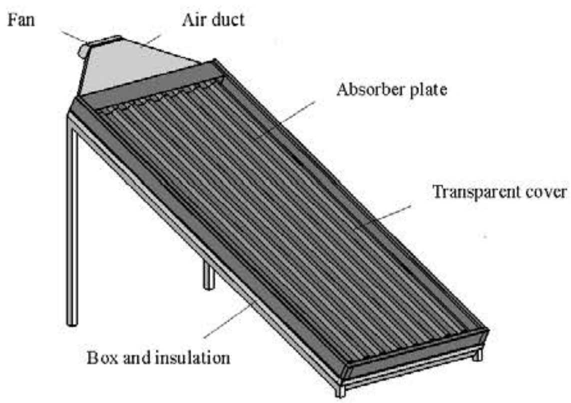

Fig. 1: Schematic view of the tested solar air collectors

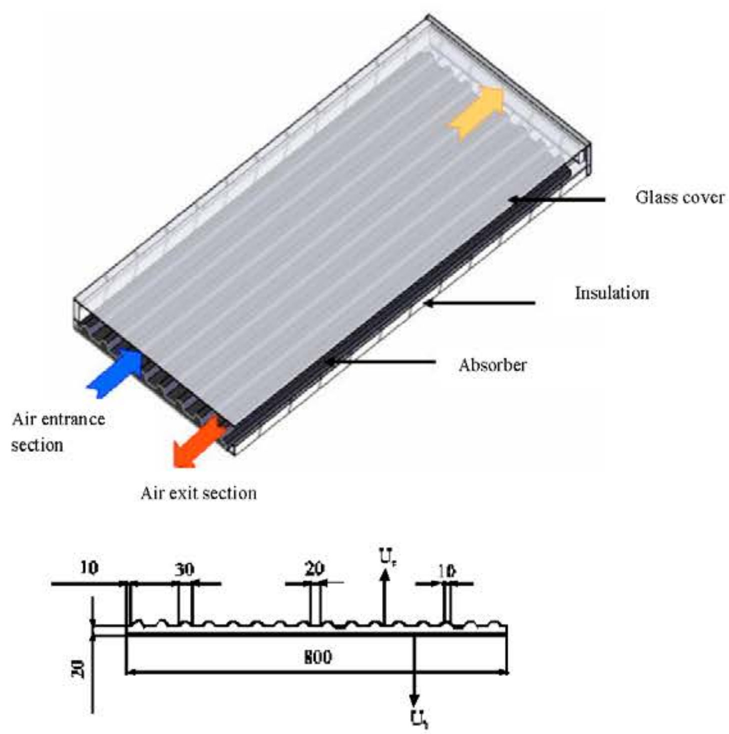

Fig. 2: Schematic view of absorber plate

humidity, air velocity. The collectors were instrumented with T-type thermocouples for measuring temperatures of the flowing air at the inlet and outlet of the collector and ambient temperature. The thermocouple, which measured the ambient temperature, was kept in a shelter to protect the sensor from direct sunlight. Temperatures were measured with accuracy of±2%. The air flow rate was calculated from the air velocity, measured by a hot wire anemometer at the collector outlet and the known duct area. Air velocity values were measured with accuracy of ±1%. The range of the velocities measured by this instrument is 0.3-35 m sec^{-1}. The air relative humidity at various points of the system was measured using hygrometer with measuring range of 5-95% and accuracy of ±2%. All the sensors used in the collector test were continuously monitored and output signals were recorded. The data acquisition system recorded the necessary data every 15 min. Air was supplied to the

Table 1: The detailed specifications of the solar air collector

Absorber material	Galvanized Sheet
Plate type	Corrugated Plate
Dimension of absorber plate	1.84×0.8m
Plate thickness	1 mm
Absorber coating	Dull black paint
Back Insulation	Glass wool (50 mm)
Side Insulation	Glass wool (50 mm)
Glazing	Normal window glass (thickness 3.8 mm)
No. of glazing	1
Sealant	Silicon rubber
Collector frame material	Stainless steel (thickness 0.5 mm)
Collector slope	36°

system by fan. The hourly intensity of solar radiation on the collector was measured locally. The collector slope was adjusted to 36°, which was considered suitable for the geographical location of Mersin.

NEURAL NETWORK MODEL

NN models represent a new method in system prediction. Neural networks differ from traditional simulation approaches in that they are trained to learn solutions rather than being programmed to model a specific problem in the normal way. A neural network consists of a number of neurons, each of which network there are three layers of neurons, i.e., input layer which receives input from the outside world, hidden layer or layers which receive inputs from the input layer neurons and the output layer which receives inputs from the hidden layers and passes its output to the outside world and in some cases back to the preceding layers. The strength of the network lies in the interconnections between the neurons which are modified during training. The training is done by exposing the network to a specific data set of information and by applying a training algorithm to enable the network to produce the desired output (Fu, 1994; Tsoukalas and Uhrig, 1996; Lin and Lee, 1996; Kalogirou, 1999a, b; Kalogirou, 2000a, b, c). In recent years, studies on applications of NN in energy systems were carried out by a number of researchers (Kalogirou and Bojic, 2000; Kalogirou, 2004a; Kalogirou, 1999; Kalogirou, 2006; Kalogirou *et al*., 1999a; Şencan *et al*., 2006; Şencan, 2006; Şencan, 2007; Şencan and Kalogirou, 2005).

In this study, a new formulation based on NN model is presented for obtaining thermal performance of solar air collector. In study, the back-propagation learning algorithm is used in a feed-forward, single hidden layer network. Logistic sigmoid transfer function is used as the activation function for both the hidden layer and the output layer. The transfer function used is presented in Eq. 19. The values of the training and test data were normalized to a range of 0 to 1. Levenberg-Marquardt (LM) Back-Propagation training was repeatedly applied until satisfactory training is achieved.

Table 2: A sample of the data set used for the training of the network (21.05.2005 date)

Time	Inlet air temperature to collector T_i (°C)	Outlet air temperature to collector T_o (°C)	Solar radiation I (W)	Air mass flow rate $\dot{m}$ (kg sec^{-1})	Thermal performance η (%)
11:30	29.6	53.0	58319.4	0.070	2.82
12:00	30.0	53.4	65778.8.	0.068	2.44
12:30	30.8	57.7	65778.8	0.069	2.83
13:00	28.9	49.7	75272.7	0.069	1.91
13:30	31.1	58.3	75272.7	0.060	2.20
14:00	32.3	58.3	69847.6	0.065	2.44
14:30	31.1	57.5	69847.6	0.053	2.00
15:00	32.7	55.5	56285.0	0.064	2.62
15:30	30.4	47.3	56285.0	0.060	1.83
16:00	31.5	46.2	42044.2	0.070	2.46
16:30	29.2	38.0	42044.2	0.065	1.37
17:00	28.9	35.2	25090.9	0.069	1.75
17:30	28.1	30.8	25090.9	0.078	0.85

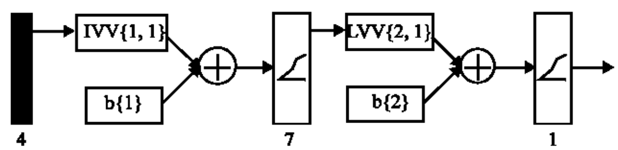

Fig. 3: NN model used for thermal performance prediction

$$F(z) = \frac{1}{1+e^{-z}} \tag{19}$$

Where:
z = The weighted sum of the input.

The computer program was performed under MATLAB environment using the neural network toolbox. The data used for the training, testing and validation of the neural network were obtained from experiments which was done at different weather conditions of Mersin for 2005 year. A sample of the data set used for the training of the network is shown in Table 2. The data set for the performance prediction of solar air collector available included 188 data patterns. From these 152 data patterns were used for the training of the network and the remaining 36 patterns were randomly selected and used as test data set.

Figure 3 shows the architecture of the NN used for the performance prediction of solar air collector. In this network, inlet and outlet air temperature to solar air collector, solar radiation and air mass flow rate are the input data and thermal performance of solar air collector is the actual output. The configuration 4-7-1 appeared to be most optimal topology for this application.

The decrease of the Mean Square Error (MSE) during the training process is shown in Fig 4. The regression curve of the output variable (thermal performance) for the

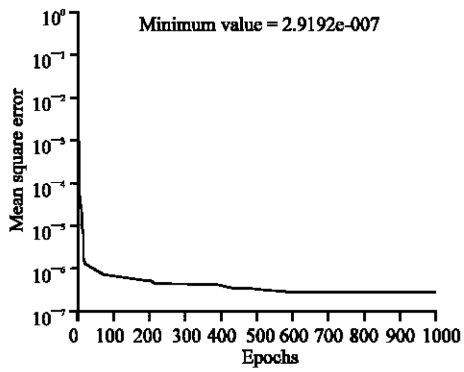

Fig. 4: Variation of mean square error with training epochs for thermal performance of solar air collector

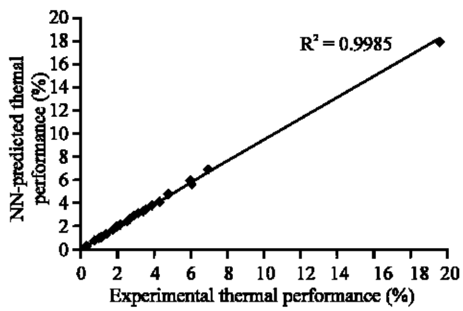

Fig. 5: Comparison of experimental and NN-predicted values of thermal performance of solar air collector for the test data set

test data set is shown in Fig 5. It should be noted that these data were completely unknown to the network. The coefficient of multiple determination (R^2-value) obtained is 0.9985 which is very satisfactory.

RESULTS AND DISCUSSION

The objective of this study was to prove whether NN can be used for the prediction of solar air collector thermal performance. In order to calculate the thermal performance of solar air collector, mathematical formulations by helping this model are derived from the resulting weights and the activation functions used in the NN. As the results obtained from both the training and testing of the NNs were extremely good in both cases it is believed that the results thus obtained would be accurate.

Mathematical formulations derived from the NN model are presented here. The best approach, which has minimum errors is, performed the LM algorithm with 7 neurons. In order to calculate the thermal performance of solar air collector, the following equations are derived:

Table 3: Weight coefficients and bias values used for the determination of the thermal performance

Neuron position (w_{ni})	I_1 (T_i)	I_2 (T_o)	I_4 (I)	I_3 ($\dot{m}$)	b_n
1	0.83445	-1.7187	1.49380	-12.2903	-2.1976
2	-1.2377	2.5730	-2.49830	17.5107	1.7328
3	-7.4176	-26.9842	41.71800	-218.4942	-16.6553
4	16.2787	-33.5867	-0.19007	-15.3285	-0.9123
5	-3.6541	7.3320	0.037911	-11.2391	4.4925
6	55.8105	-30.0595	58.72860	-68.0250	-20.4646
7	-1.6929	2.8910	-7.50390	13.4746	-4.2537

Note: In weights n represents input number and i represent hidden neuron number

Table 4: Normalization coefficients for the input parameters

Input parameter	Coefficient
Inlet air temperature to collector (T_i)	40
Outlet air temperature to collector (T_o)	80
Solar radiation (I)	85000
Air mass flow rate ($\dot{m}$)	1
Output parameter	
Thermal performance of collector (η)	20

Note: The actual values are divided with the above coefficients to obtain the normalized values

$$E_i = \sum_{n=1}^{4} I_n w_{ni} + b_n \tag{20}$$

$$F_i = \frac{1}{1+e^{-E_i}} \tag{21}$$

In the above equations for E_i the first two values are the multiplication of the input parameters (I_n) with their weights at location n and the last constant value (b_n) represents the bias term. The subscript i represents number of hidden neuron. The four input parameters are:

I_1 = Inlet air temperature to collector (T_i)
I_2 = Outlet air temperature to collector (T_o)
I_3 = Solar radiation (I)
I_4 = Air mass flow rate ($\dot{m}$)

In the NN seven hidden neurons are used, thus seven pairs of equations, i.e., E_1 to E_7 and F_1 to F_7 are required, which represent the summation and activation functions of each neuron of the hidden layer, respectively. The coefficients of Eq. 15 are given in Table 3.

Additionally, the actual input data of the various parameters need to be normalized in the range of [0 to 1]. For this purpose the actual values of each parameter are divided with the coefficients shown in Table 4.

Finally, the thermal performance of solar air collector depending on inlet and outlet air temperature to collector, solar radiation and air mass flow rate values can be computed from:

$$E_8 = F_1*(-67.9276)+F_2*(-20.6039)+F_3*(6.5086) +F_4*(-16.2211) +F_5*(74.9805)+ F_6*(-6.9735) +F_7*(60.5512) - 46.5051$$

$$\eta = \left(\frac{1}{1+e^{-E_8}}\right).20 \quad (23)$$

Table 5: Comparison of the experimental and NN results for the thermal performance at 18.05.2005 date

Time	Experimental thermal performance (%)	Predicted thermal performance (%)	Error
12:00	3.97	3.9672	0.0028
12:30	3.17	3.1729	-0.0029
13:00	2.96	2.9721	-0.0121
13:30	2.85	2.8474	0.0026
14:00	2.94	2.9420	-0.0020
14:30	2.73	2.7269	0.0031
15:00	3.56	3.5639	-0.0039
15:30	3.17	3.1745	-0.0045
16:00	4.52	4.5195	0.0005
16:30	4.44	4.4364	0.0036
17:00	5.91	5.7009	0.2091

Table 6: Comparison of the experimental and NN results for the thermal performance at 19.05.2005 date

Time	Experimental thermal performance (%)	Predicted thermal performance (%)	Error
09:00	3.47	3.4753	-0.0053
09:15	2.76	2.7635	-0.0035
09:30	3.39	3.3969	-0.0069
09:45	3.77	3.7739	-0.0039
10:00	3.65	3.6475	0.0025
10:15	3.72	3.7176	0.0024
10:30	3.11	3.1064	0.0036
10:45	3.14	3.1337	0.0063
11:00	3.30	3.2970	0.0030
11:15	3.66	3.6617	-0.0017
11:30	3.30	3.2953	0.0047
11:45	3.55	3.5597	-0.0097
12:00	3.09	3.0939	-0.0039
12:15	3.27	3.2702	-0.0002
12:30	3.32	3.2700	0.0500
12:45	3.08	3.0810	-0.0010
13:00	3.07	3.0744	-0.0044

Table 7: Comparison of the experimental and NN results for the thermal performance at 20.05.2005 date

Time	Experimental thermal performance (%)	Predicted thermal performance (%)	Error
13:45	2.62	2.6103	0.0097
14:00	2.86	2.8804	-0.0204
14:15	3.41	3.4298	-0.0198
14:30	2.71	2.7262	-0.0162
14:45	3.15	3.1567	-0.0067
15:00	3.81	3.8133	-0.0033
15:15	3.42	3.4046	0.0154
15:30	3.10	3.0874	0.0126
15:45	2.59	2.6030	-0.0130
16:00	4.99	4.9657	0.0243
16:15	4.90	4.9229	-0.0229
16:30	4.17	4.1670	0.0030
16:45	4.10	4.1178	-0.0178
17:00	3.48	3.4768	0.0032

The coefficient shown in Eq. 23 is used to convert the normalized output to actual output (η) of solar air collector.

In Table 5-11, comparisons for thermal performance of solar air collector between the NN-predicted results and the experimental values for different days of May month are presented. As can be seen in these figures, thermal performance values obtained from the NN method are

Table 8: Comparison of the experimental and NN results for the thermal performance at 21.05.2005 date

Time	Experimental thermal performance (%)	Predicted thermal performance (%)	Error
11:30	2.82	2.8354	-0.0154
12:00	2.44	2.4399	0.0001
12:30	2.83	2.8458	-0.0158
13:00	1.91	1.9273	-0.0173
13:30	2.20	2.1867	0.0133
14:00	2.44	2.4386	0.0014
14:30	2.00	2.0369	-0.0369
15:00	2.62	2.6187	0.0013
15:30	1.83	1.8259	0.0041
16:00	2.46	2.4629	-0.0029
16:30	1.37	1.3879	-0.0179
17:00	1.75	1.7442	0.0058
17:30	0.85	0.8513	-0.0013

Table 9: Comparison of the experimental and NN results for the thermal performance at 22.05.2005 date

Time	Experimental thermal performance (%)	Predicted thermal performance (%)	Error
13:00	1.70	1.7001	-0.0001
13:15	2.49	2.4970	-0.0070
13:30	2.47	2.4630	0.0070
13:45	2.51	2.5120	-0.0020
14:00	2.89	2.8672	0.0228
14:15	2.50	2.4868	0.0132
14:30	2.95	2.9390	0.0110
14:45	3.03	3.0280	0.0020
15:00	3.25	3.2317	0.0183
15:15	3.20	3.1834	0.0166
15:30	2.98	3.0009	-0.0209
15:45	3.01	3.0112	-0.0012
16:00	2.53	2.5514	-0.0214
16:15	1.73	1.7277	0.0023
16:30	1.06	1.0595	0.0005

Table 10: Comparison of the experimental and NN results for the thermal performance at 24.05.2005 date

Time	Experimental thermal performance (%)	Predicted thermal performance (%)	Error
09:00	1.31	1.3758	-0.0658
09:30	1.7	1.7026	-0.0026
10:00	2.01	2.0246	-0.0146
10:30	2.24	2.2305	0.0095
11:00	2.19	2.1939	-0.0039
11:30	2.09	2.0918	-0.0018
12:00	2.77	2.7836	-0.0136
12:30	2.68	2.6681	0.0119
13:00	2.19	2.1865	0.0035
13:30	1.05	1.0406	0.0094
14:00	0.7	0.7036	-0.0036
14:15	0.62	0.6157	0.0043

Table 11: Comparison of the experimental and NN results for the thermal performance at 31.05.2005 date

Time	Experimental thermal performance (%)	Predicted thermal performance (%)	Error
12:30	3.56	3.5575	0.0025
13:00	6.88	6.8436	0.0364
13:30	6.54	6.5626	-0.0226
14:00	4.75	4.7128	0.0372
14:30	5.10	5.1072	-0.0072
15:00	3.07	3.0862	-0.0162
15:30	3.39	3.3927	-0.0027
16:00	4.73	4.7423	-0.0123
16:30	3.73	3.7451	-0.0151
17:00	5.28	5.2762	0.0038
17:30	2.07	2.0718	-0.0018
17:45	1.31	1.3047	0.0053

very close to the experimental values. In Table 5-11, the differences between experimental and NN results are maximum 0.2091, 0.05, 0.0243, 0.0179, 0.0228, 0.0658 and 0.0372, respectively. In these tables, thermal performance values slightly differ from because of cloudy of air and wind velocity in the some time.

CONCLUSIONS

In this study, NN is used as a new approach for the determination of thermal performance of solar air collector. Experimental data were used for training and testing of the networks. The NN is successfully applied to determine of thermal performances of solar air collector. The R^2 value is about 0.9985, which can be considered as very satisfactory. In study, in order to calculate the thermal performance values, mathematical formulations were derived from the NN model. Mathematical formulations have been obtained from formulations of the summation and activation functions used in the NN model and weights of neurons. The thermal performance of solar air collector with use of this new formulation can be estimated simply and quickly. The advantages of the NN method are the faster, simpler solutions and the avoidance of the need to perform long series of collector performance tests. Also this method can be applied to determine thermal performance of different collector types and different applications in the energy systems. Thus the performance analysis of solar collectors can be simplified. Accuracy and usefulness of NN method can be increased with more data.

NOMENCLATURE

A_c = Collector surface area (m^2).
c_p = Specific heat of air (J/kg K).
E_i = Summation function of neuron i.
F_i = Activation function of neuron i.
F_R = Collector heat removal factor.
F' = Collector efficiency factor.
k = Thermal conductivity of insulator (W/m K).
L = Thickness of the insulator (m).
Lc = Collector length (m).
$\dot{m}$ = Mass flow rate (kg sec^{-1}).
h_1 = Heat convection coefficient between the glass cover and air (W/m^2 K).
h_2 = Heat convection coefficient between the absorber plate and air (W/m^2 K).
h_r = Radiation coefficient between the air-duct surfaces (W/m^2 K).
h_s = Heat convection coefficient between the insulation and ambient (W/m^2 K).
h_w = Heat convection coefficient for air flowing over the outside surface of the glass cover (W/m^2 K).
I = Total solar radiation incident on collector (W/m^2).
N = No. of glass cover.
Nu = Nusselt number.
Q_u = Collector useful energy (W).
Re = Reynolds number.
T = Temperature (K).
U_b = The bottom heat loss coefficient (W/m^2 K).
U_e = The edge heat loss coefficient (W/m^2 K).
U_L = The collector overall heat loss coefficient (W m^2 K).
U_t = The top heat loss coefficient (W/m^2 K).
V = Wind velocity (m sec^{-1}).
W_c = Collector width (m).
H = Collector efficiency.
ε_g = Emissivity of the glass cover.
ε_p = Emissivity of the absorbing plate.
β = Collectors tilt (degree).
ρ = Density of air (kg m^{-3}).
$(\tau\alpha)$ = Effective transmission.
σ = Stefan Boltzmann constant $=2.04\times10^{-7}$ (kJ s m^{-2} K^4).

SUBSCRIPTS

a = Ambient
f = Fluid
I = Inlet
o = Outlet
p = Absorbing plate
r = Radiation
s = Sun

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