Desalination and Water Treatment
www.deswater.com
doi:10.5004/dwt.2017.20356

73 (2017) 80–89
April

Optimal operating condition for a type parabolic trough collector with low-cost components using inverse neural network and solved by genetic algorithm

E.D. Reyes-Téllez[a], R.A. Conde-Gutiérrez[a,*], J.A. Hernández[b,*], E. Cardoso[a], S. Silva-Martínez[b], F. Z. Sierra[b], O. Cortés-Aburto[c]

[a]*Posgrado del Centro de Investigación en Ingeniería y Ciencias Aplicadas (CIICAp) de la Universidad Autónoma del Estado de Morelos. Av. Universidad No. 1001, Col Chamilpa, CP. 62209, Cuernavaca, Morelos, México, email: roberto.conde@uaem.mx (R.A. Conde-Gutiérrez)*
[b]*Centro de Investigación en Ingeniería y Ciencias Aplicadas (CIICAp), Universidad Autónoma del Estado de Morelos (UAEM). Av. Universidad No. 1001, Col Chamilpa, CP. 62209, Cuernavaca, Morelos, México, Tel. +52 01 777 3297084 email: alfredo@uaem.mx (J.A. Hernández)*
[c]*Universidad Politécnica de Puebla, Tercer Carril del Ejido "Serrano" s/n, San Mateo Cuanalá, Juan C. Bonilla, Puebla, C.P. 72640*

Received 28 June 2016; Accepted 16 November 2016

ABSTRACT

The parabolic trough collectors (PTC) are able to concentrate the solar radiation and in turn transferred heat along a tube. In this paper, the PTC uses copper tube to heat water in residential use, which reduced costs in the system. An artificial neural network (ANN) model was developed to predict the hot-water outlet temperature of PTC with low-cost components, and its inverse (ANNi) was used to optimize the system's performance. The best fitting training data was acquired with the architecture of 9-9-1 considering a hyperbolic tangent sigmoid transfer-function in the hidden layer and a linear transfer-function in the output. Comparing the predicted and experimental data it was observed a satisfactory agreement ($R^2 > 0.9854$, RMSE > 0.8055 and MAE ~0.0586). Furthermore, from this ANN model, a strategy was applied for optimize the feeding tank temperature, in order to increase the water outlet temperature of the PTC, using inverse artificial neural networks (ANNi) and solved by the method of genetic algorithms (GAs). These results showed that the highest outlet temperature reached by the PTC was 49°C. Consequently a good prediction of the ANN model, as well as the optimized data using ANNi-GAs, makes it possible to control on-line the operation of the system and improve performance.

Keywords: Parabolic trough collector with low-cost components; Increase of water temperature; Inverse artificial neural network; Genetic algorithms; Optimal values

1. Introduction

Currently, the exploitation of flat panel solar thermal collectors has assumed a great importance not only in residential applications, but also in industrial and commercial buildings, where low temperature hot-water is required and particularly for hot climates [1].

However, in the search at increase efficiency in these equipment, they have become more expensive, due to the materials used for its manufacture, making them inaccessible to the residential areas of low economic resources, in where only is required to increase the temperature of the water to meet their daily needs.

Apart of the flat panel solar collectors, there are also of type parabolic, which has the capability to absorb the solar

*Corresponding author.

Presented at the EDS conference on Desalination for the Environment: Clean Water and Energy, Rome, Italy, 22–26 May 2016.

radiation and convert it to heat, transferring it to the working fluid. The working fluid to be heating can be maybe air, water, oil or some organic solvents. The heat energy which is in the form of thermal energy in the working fluid of the solar collector can directly be utilized for different applications [2].

The parabolic trough collectors (PTC) are one possible option for use in residential areas, as they can be made with inexpensive materials and feasible for installation in low-income communities. In this work, this type of collector is elected in specific because the materials used can be found in any region (copper tube and concentrator of steel), in order to have a long shelf life by his resistance, in comparison with other fragile materials.

In this work, we study the description of experimental equipment PTC with low-cost components. In addition, simulate the obtained experimental data with an artificial neural network (ANN) model. ANN has been widely used to simulate diver's solar collectors, as: Kalogirou [3] used the artificial neural networks for the prediction of the performance parameters of flat-plate solar collectors. Sözen et al. [4] studied a new formula based on artificial neural network technique which was developed to determine the efficiency of flat plate solar collectors, where the surface temperature in collector, date, time, solar radiation, declination angle, azimuth angle and tilt angle are used in the input layer of the network and the efficiency of flat-plate solar collector was in the output layer. Caner et al. [5] used an artificial neural network model to estimate thermal performances of solar air collectors for two types of solar air collectors, calculated values of thermal performances are compared to predict values and the results demonstrate effectiveness of the proposed ANN. Fischer et al. [6] realized a comparison between state-of-the-art and neural network modeling of solar collectors. The obtained results showed better agreement between measured and calculated collector output for the artificial neural network approach compared with the state-of-the-art modelling.

Consequently, once simulated the experimental data using ANN, it is necessary to know the optimal conditions in the input variables for the PTC in order to deliver better results. Inverse artificial neural network (ANNi) is an essential element to calculate the optimal operation conditions. This model uses the same weights and bias obtained during training ANN model and has been used in experimental equipment in order to improve performance, such as: Laidi et al. [7] used this kind of methodology to determine the optimal solar COP value of a solar-assisted adsorption refrigeration system working with activated carbon/methanol as working pairs, where this methodology was applied to find optimal input parameter for the required solar COP. Hattab et al. [8] developed and tested an inverse artificial neural network model for the prediction of the optimal soil treatment to reduce copper (Cu) toxicity assessed by a given target concentration of Cu in dwarf bean leaves (BL) from selected soil inputs. Morales et al. [9] developed an artificial neural network (ANN) model to predict the coefficient of performance (COP) of an absorption heat transformer with a new physical design consisting of compact components and they applied a model of inverse artificial neural network to optimize the value of COP, showing an increase in COP of 0.35–0.40, finding the optimal conditions in the inlet temperatures generator and for evaporator.

In this work, the water outlet temperature (T_{out}) of the PTC is chosen as a required value, as it is considered a general variable to determine the performance system, but to know this value, depends on the variables of system, such as: the feeding tank temperature (T_{feed}),the storage tank temperature of the water hot (T_{sto}), inlet temperature to the solar collector (T_{in}), month (m), day (d), total time (t), ambient temperature (T_{amb}), surface temperature to glass solar collector (T_{surf}) and the temperature of reflector surface (T_{ref}), which some of these input variables can be optimized to increase the performance of the PTC.

The aim of the present work was to develop a strategy to optimally control of a parabolic trough collector with low-cost components. In this case, the input condition to optimize the system was the feeding tank temperature (T_{feed}). This inlet variable was optimized using the methodology of ANNi and solved by the genetic algorithms (GAs). It is interesting mention the identification of this parameter, since this was supplied to the equipment and can be regulated directly, unlike other input variables that depend on climatic conditions. Determining optimal conditions of input variables may increase the T_{out} value, in order to know the maximum water temperature at the outlet of PTC and determine that domestic activities can be performed with the temperature interval.

2. Description of experimental equipment

A static collector with solar type-parabolic concentrator of foil reflective plate 316L stainless steel 16 gauge with mirror polishing the inside was installed as shown in Fig. 1. This solar collector was chosen because it was the most viable to have better results in collection performance (37%) and better usable thermal energy (and includes losses) with 50.5 kW [10].

The concentrator consists of a steel sheet drum vertically cut with dimensions of 85 cm long by 57 cm diameter (see Fig. 1). The receiving surface was constituted of a copper tube of 1.27 cm diameter (½ inch) by 90 cm long and was painted black to have a higher absorptivity.

To avoid convective losses and take advantage of the greenhouse effect, it has a glass cover of 85 cm long by 57 cm wide, with an aluminum frame.

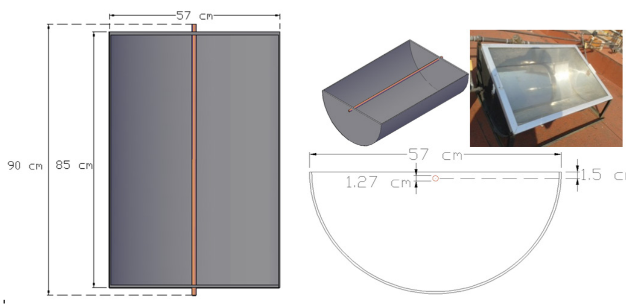

Fig.1. Dimensions with front and side view of the PTC system.

This PTC was instrumented with thermocouples type T properly calibrated to measure temperature in the following region (see Fig. 2):

1. At the entrance of the copper tube
2. At the output of the copper tube
3. In the reflective surface
4. On the surface of the glass plate
5. One atmospheric

An acquisition card *Agilent 34970A* was used and by *Benchlink Data Logger* software was saved and stored the previously described temperatures with date and time to create the database.

Fig. 2 shows that the system comprises a feed tank (cold water) and storage tank of hot water (thermo-tank) of 750 and 450 L, respectively. They are interconnected to have recirculation and thus raise the temperature of the feed tank when hot water will not be in use.

2.1. Operating conditions

The type-parabolic trough collector was fixed and the entire system was located on the facilities of CIICAp-UAEM in the State of Morelos, in the city of Cuernavaca; with latitude and longitude coordinates of 18.981655, –99.23418 respectively. Its orientation was East-West with the face of the reflector plate pointing South. It has 19° inclination to better exploit the incidence of solar radiation, according to the latitude.

Experimental tests were performed with a flow rate of 1 LPM sanitary water for common use. For this, the shut-off valves were regulated and according to the flow meter to maintain this constant flow throughout the duration of the test. Table 1 shows the operating conditions which were applied in the PTC experimental.

Table 1
Interval of experimental operating conditions used to obtain the T_{out} values

Experimental variables	Working interval
Inputs	
Month	1–12
Day	1–31
Time, s	20267–69085
Temp. input, °C	9–50.01
Temp. ambient, °C	9.07–70.28
Temp. surface, °C	9.53–51.4
Temp. reflectance, °C	9.05–77.92
Temp. feed, °C	13.14–30.35
Temp. storage, °C	13.57–54.07
Output	
Temp. output, °C	9.73–50.67

The hours, at which the tests were started and ended, were varied, taking the earliest time of day at 5:30 h while the later was at 19:10 h. The most common start and end of test was 9:00 has 17:30 h. The interval between measurements was 10 s. These tests were conducted in the months of May and June (spring and summer) of 2014 and January 2016 (winter) [11].

3. Development of the neural network model

The artificial neural network model (ANN) was integrated with k inputs, where each input (In_i) was assigned with an appropriate coefficient called weight (W_i). The sum

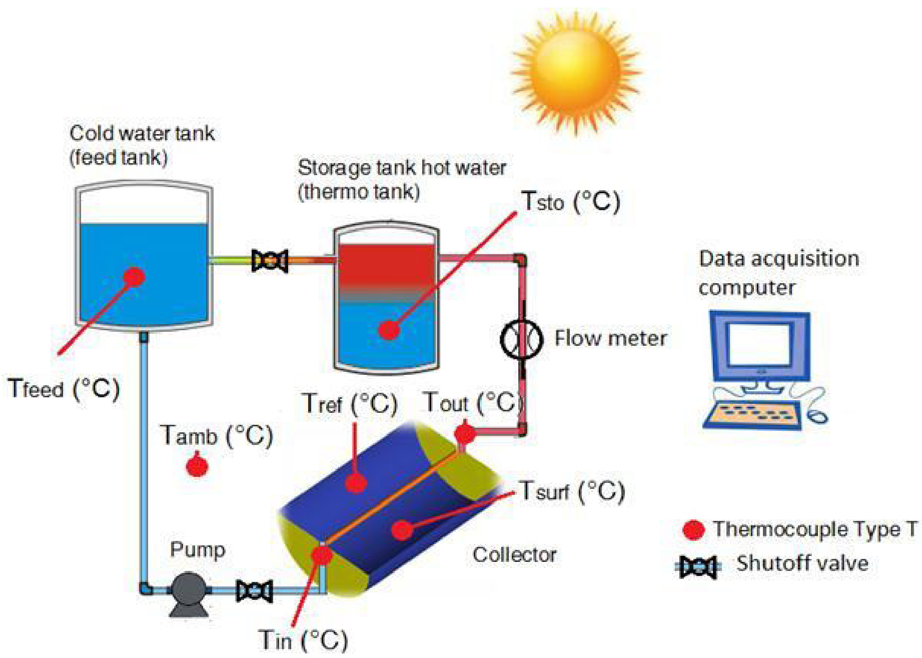

Fig. 2. Schematic diagram of experimental system PTC with low-cost components.

of the inputs, weights and biases b generate the argument (n_s) [see Eq. (1)] to be applied at a transfer-function which will generate an output.

$$n_s = Wi_{(s,1)} \times In_1 + Wi_{(s,2)} \times In_2 + ... + Wi_{(s,k)} \times In_k + b_{(1,s)} \quad (1)$$

The weights *(Wi)* and biases (b_1) are coefficients connected with the input-hidden layers which are grouped into matrices. For the output-layer, the weighted sum of the signals provided by the hidden layer, and the associated coefficients were grouped into matrices Wo and b_2. In the hidden layer, the hyperbolic tangent transfer function (TANSIG) was applied and in output layer was used the linear transfer function (PURELIN) to had a better prediction with respect to the experimental data. All calculations were carried out with Matlab mathematical software with the ANN toolbox.

In order to ANN model development, it was carried out through three general tasks [12] (see Fig. 3):

i) Divide randomly the database experimental (69,047) into training (50%), testing (25%) and validation (25%). These data was sufficient to train and test the ANN model.
ii) Development and evaluation of ANN models, for the reliable prediction of the outlet temperature of hot water of PTC.
iii) Comparative statistical analysis between experimental data and predicted T_{out} (inferred from the application of the ANN tools).

It is important to mention that the input parameters were normalized ($x_{i,Norm}$) in the range (0, 0.9) as follows [13]:

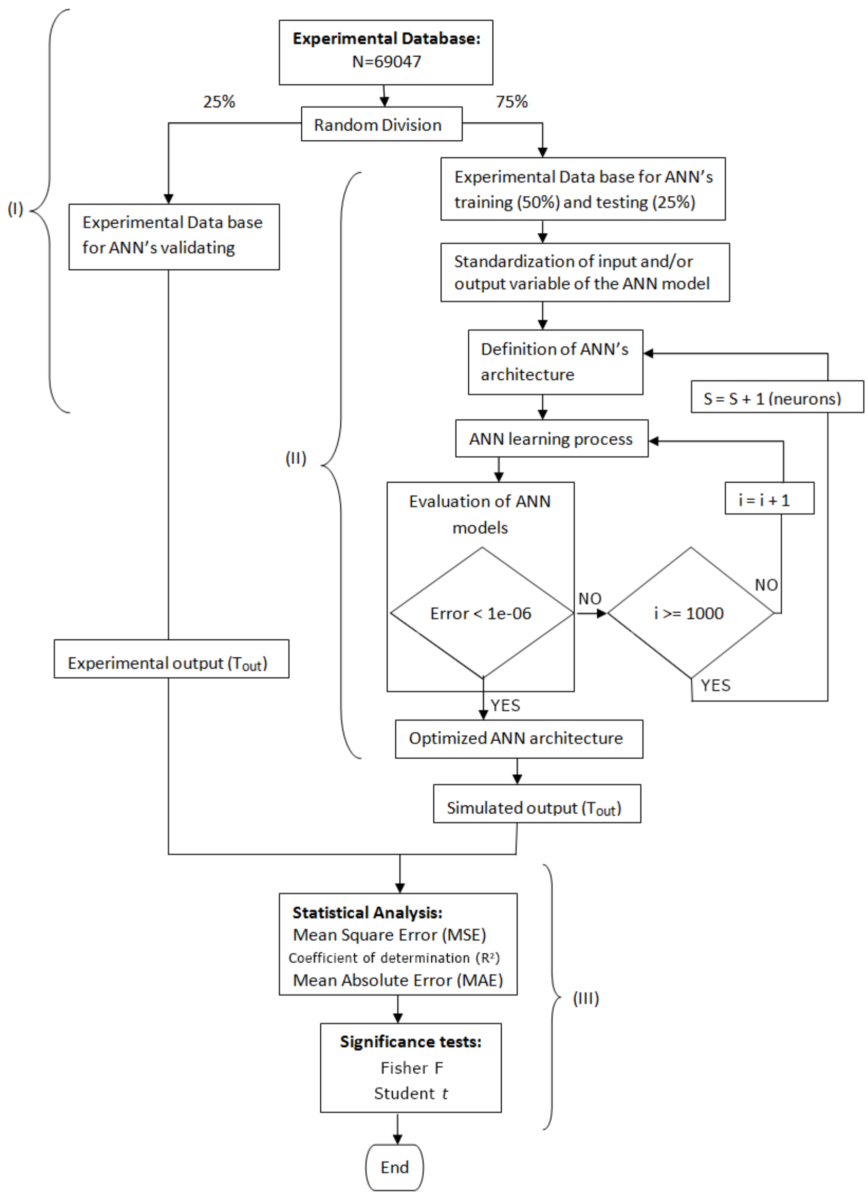

Fig. 3. Schematic methodology [modified from 12].

$$x_{i,Norm} = 0.8 \times \left(\frac{X_{i,\mathrm{Re}al} - X_{\min}}{X_{\max} - X_{\min}} \right) + 0.1 \quad (2)$$

ANN was normally trained for leading a particular input to predict an output target. For minimizing the differences between the output target (given by experimental data) and simulated output (generated by a weight adjusting process), the back-propagation optimization algorithms using the Levenberg–Marquardt algorithm (see Fig. 4), was considered by Hagan and Menhaj [14,15] as the most efficient and it was widely preferred [16]. The root mean square error (RMSE) was applied as an optimization criterion in training for the adjustment ANN model.

In order to corroborate the adaptability of the ANN model was compared experimental data and simulated applying the following statistical test parameters: root mean square error (RMSE), mean absolute error (MAE) and the coefficient of determination(R^2) [17].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(P_{Sim(i)} - P_{Exp(i)} \right)^2}{n}} \quad (3)$$

$$MAE = \sum_{i=1}^{n} \frac{\left| P_{Sim(i)} - P_{Exp(i)} \right|}{P_{Exp(i)}} \quad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (P_{Exp(i)} - P_{Sim(i)})^2}{\sum_{i=1}^{n} (P_{Exp(i)} - \bar{P}_{Exp})^2} \quad (5)$$

where $\bar{P} = \frac{1}{n}\sum_{i=1}^{n} P_i$; $P_{Sim(i)}$ was the value estimated by ANN; $P_{Exp(i)}$ was the experimental value of the variable (T_{out}).

Finally, the comparison of the simulated database by ANN and the experimental database was applied the tests of the relationship Fisher F and Student t for confirm the adequacy of the model. The aim was to analyze statistically: if the two databases have the same or similar variances (test Fisher-F); or if the two databases belong to the same population or similar populations through its mean (test Student-t) [18].

$$F = \frac{S_x^2}{S_y^2} \quad (6)$$

$$t = \frac{\left| \bar{x} - \bar{y} \right|}{s\left(\sqrt{\left(\frac{1}{nx} + \frac{1}{ny} \right)} \right)} \quad (7)$$

4. Neural network model

An ANN model with nine neurons in the hidden layer was found to be efficient in predicting T_{out} values for a parabolic trough collector with low-cost components. Different numbers of neurons in the hidden layer were tested to determine the best architecture of the ANN model. Table 2 provides a comparison between the transfer function (TANSIG) and the error for T_{out} predicted by an ANN model.

According to data obtained by the ANN training, the best values for RMSE, MAE and R^2 were 0.8055, 0.0586, and 0.9854, respectively. Fig. 5 presents a comparison between the predicted and experimental data of the T_{out} values, using all data (training, testing and validation). Experimental T_{out} Exp and simulated T_{out} Sim data were compared satisfactorily through a linear regression model [T_{out}Sim = 0.98542*T_{out} Exp + 0.44038].

Table 3 shows the test from the relationship Student t and Fisher F, where the hypothesis null H_0 is accepted for both tests showed. The results in the two samples have the same variance and the means of the samples are equal, indicating that the sample comes from the same population.

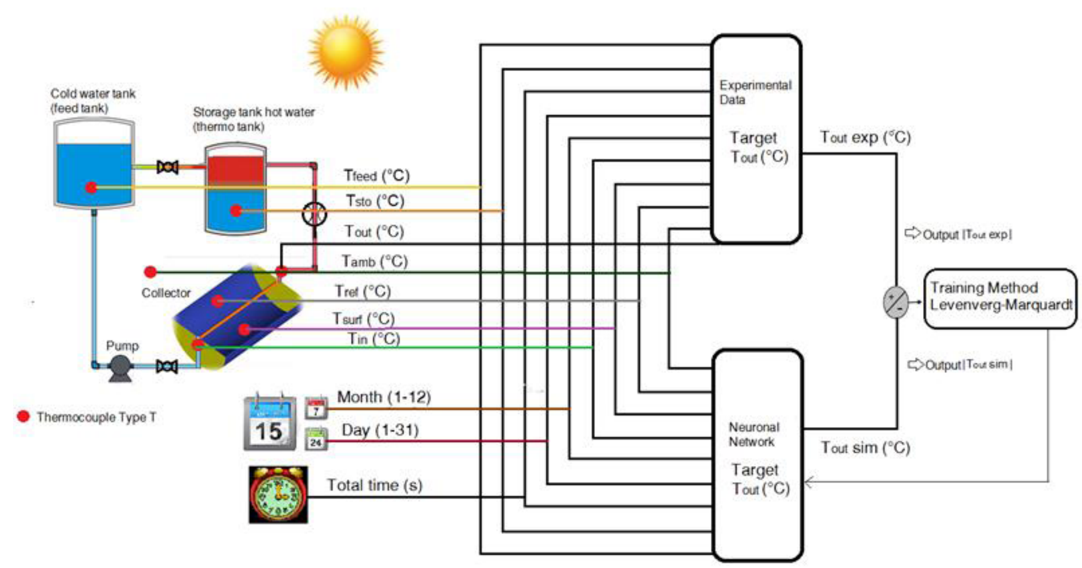

Fig. 4. Applied network architecture for T_{out} values and procedure used for neural network learning.

Table 2
Tests with different architectures ANN

Architecture ANN	Number of neurons	Epoch	Coefficient of determination	Root mean square error	Mean absolute error	Root mean square error	Mean absolute error
			(R^2)	(RMSE)	(MAE)	(RMSE)	(MAE)
			TANSIG			Data Training	
9-1-1	1	1000	0.9158	1.9373	0.3969	1.3697	0.3975
9-2-1	2	1000	0.9461	1.5492	0.2131	1.0956	0.2140
9-3-1	3	1000	0.9587	1.3560	0.1729	0.9586	0.1728
9-4-1	4	1000	0.9693	1.1695	0.1350	0.8277	0.1353
9-5-1	5	1000	0.9712	1.1335	0.1296	0.8018	0.1285
9-6-1	6	1000	0.9751	1.0532	0.1041	0.7458	0.1057
9-7-1	7	1000	0.9786	0.9764	0.1000	0.6905	0.0995
9-8-1	8	1000	0.9808	0.9244	0.0897	0.6540	0.0909
9-9-1	9	1000	0.9854	0.8055	0.0586	0.5700	0.0603
9-10-1	10	1000	0.9851	0.8140	0.0651	0.5763	0.0673

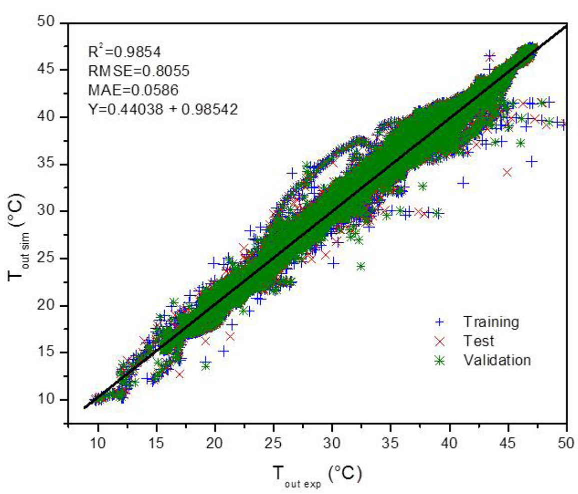

Fig. 5. Statistical comparison between simulated (ANN) and experimental T_{out} data.

Table 3
Application of significance tests from relationship Fisher *F* and Student *t*

Test Fisher *F*	Test Student *t*
F (Inflicted Eq. 6) 1.0146	*t* (Inflicted Eq. 7) 0.1161
Fc (Inflicted from statistical tables 99%) 1.0178	*tc* (Inflicted from statistical tables 99%) 2.3264
Comparison 1.0146 < 1.0178	Comparison 0.1161 < 2.3264
The null hypothesis H_0 is accepted " $S_x^2 \approx S_y^2$ "	The null hypothesis H_0 is accepted " $\overline{x} \approx \overline{y}$ "

Table 4 presents the adjustable parameters (*Wi, Wo,* b_1 and b_2) of the proposed model. Consequently, these coefficients are used in the ANN model to simulate T_{out} values.

Basing on the best structure of ANN (9 neurons in the hidden layer) and a transfer function (TANSIG), the proposed model can be analytically represented by the following Eq. (8):

$$T_{out} = \sum_{j=1}^{S}\left[W_o(j)\cdot\left(\frac{2}{1+\exp\left(-2\cdot\left(\sum_{k=1}^{K}(W_i(j,k)\cdot In(k))+b1_{(j)}\right)\right)}-1\right)\right]+b2 \quad (8)$$

where *s* is the neurons number in the hidden layer (*s* = 9), *k* is the neurons number in the input layer (*k* = 9), and *W* and *b* are weights and biases, respectively (see Table 4).

This model after being compared and analyzed statistically, we can be successfully used for simulation and control on-line of the experimental equipment, as it is shown in Fig. 6, which is compared the T_{out} values with respect to the time of day, where it is observed that the highest values of T_{out} reached in the period of 12 to 16 h, due to region and sunlight. With ANN model, was observed a good agreement between predicted values and experimental data points. This confirmed the adequacy of the ANN to carry out the simulation from the hot water outlet temperature for a parabolic trough collector with low-cost components.

5. Development of the inverse neural network model

This methodology was used to calculate optimum operating conditions at the input variables of experimental equipment to obtain better results [19]. Starting from Eq. (8), if output the T_{out} was known, it can find an optimal input variable (*k*), as shown in the following steps:

First develop the equation of the T_{out} from the ANN model, with nine neurons, with their weights and bias, respectively.

$$\mathrm{T}_{out} = 2\left[\begin{array}{l}\frac{W_{0(1,1)}}{1+\exp(x_1)}+\frac{W_{0(1,2)}}{1+\exp(x_2)}+\frac{W_{0(1,3)}}{1+\exp(x_3)}+\frac{W_{0(1,4)}}{1+\exp(x_4)}\\ +\frac{W_{0(1,5)}}{1+\exp(x_5)}+\frac{W_{0(1,6)}}{1+\exp(x_6)}+\frac{W_{0(1,7)}}{1+\exp(x_7)}+\frac{W_{0(1,8)}}{1+\exp(x_8)}+\frac{W_{0(1,9)}}{1+\exp(x_9)}\end{array}\right] \quad (9)$$
$$-\left(W_{0(1,1)}+W_{0(1,2)}+W_{0(1,3)}+W_{0(1,4)}+W_{0(1,5)}+W_{0(1,6)}+W_{0(1,7)}+W_{0(1,8)}+W_{0(1,9)}\right)+b2$$

Table 4
Weighting and bias parameters obtained for the ANN model developed

Number of Inputs	Hidden layer weight *Wi* (*k*,*s*)								
(*k*)	(*s* = 1)	(*s* = 2)	(*s* = 3)	(*s* = 4)	(*s* = 5)	(*s* = 6)	(*s* = 7)	(*s* = 8)	(*s* = 9)
1	–7.47223	–45.43951	–23.35323	–28.32771	8.04169	6.66546	6.94243	–9.03039	132.64311
2	–4.33701	0.01231	6.69262	–3.32465	0.42654	0.80512	3.23766	1.83490	–0.08478
3	0.19145	0.66056	–0.98259	1.55410	–1.23535	–0.16123	0.45906	0.57498	0.64693
4	–49.39705	11.99704	–5.02621	–36.71076	–19.01847	2.39624	25.20531	27.59983	13.66471
5	13.39573	12.11535	7.49851	–15.02677	–9.06184	–2.68765	8.22856	2.31844	4.25276
6	–30.41051	–37.72298	–50.21982	16.61051	–7.70863	8.37961	–27.39636	–43.31220	266.32813
7	8.39629	–1.98483	–1.20287	11.43457	5.90166	–1.24893	–4.12611	–8.70573	–4.95515
8	4.88839	–5.00822	3.21137	8.65863	4.98912	–2.18178	–3.74167	–7.26927	–12.09112
9	–46.48324	6.28701	–25.30987	10.58262	–20.10860	–0.48387	–9.75767	18.70274	–14.01995
Output layer weights (*l* = 1) *W0* (*s*,*l*)									
s,1	1.96232	6.55676	21.17485	3.29298	–2.98869	–1.59993	3.95455	4.29601	–2.13722
Bia b1(*s*)	28.05543	–2.35558	–0.75726	37.70280	–18.33455	18.67116	–1.07319	0.33432	52.19837
Bia b2(*l* = 1)	22.14903								

**s* is the number of neurons in the hidden layer, *k* is the number of neurons in the input layer, *l* is the number of neurons in output layer (*l = 1*).

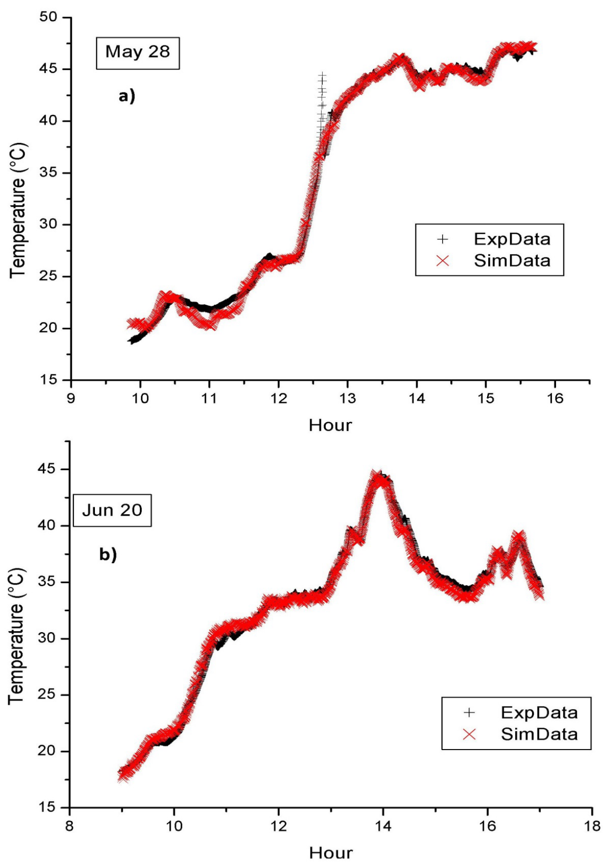

Fig. 6. Comparison of the hot water outlet temperature of PTC between experimental and simulated by ANN, with respect to the time of day a) for May, b) for June.

where in (x) you can choose any of the 9 available input variables (k), to know its optimum value and observe the results obtained with respect to T_{out}.

$$x_1 = -2\cdot\begin{pmatrix} W_{i(1,1)}\cdot k1 + W_{i(1,2)}\cdot k2 + W_{i(1,3)}\cdot k3 + W_{i(1,4)}\cdot k4 + W_{i(1,5)}\cdot k5 \\ + W_{i(1,6)}\cdot k6 + W_{i(1,7)}\cdot k7 ... + W_{i(1,8)}\cdot k8 + W_{i(1,9)}\cdot k9 + b1_{(1)} \end{pmatrix} \quad (10)$$

$$x_9 = -2\cdot\begin{pmatrix} W_{i(9,1)}\cdot k1 + W_{i(9,2)}\cdot k2 + W_{i(9,3)}\cdot k3 + W_{i(9,4)}\cdot k4 + W_{i(9,5)}\cdot k5 \\ + W_{i(9,6)}\cdot k6 + W_{i(9,7)}\cdot k7 ... + W_{i(9,8)}\cdot k8 + W_{i(9,9)}\cdot k9 + b1_{(9)} \end{pmatrix} \quad (11)$$

In this work, it was important identify parameters of operation through ANNi, in order to set an optimal value. In this case, the feeding tank temperature was elected, since this variable can be regulated directly by a valve and according with optimization you can vary the temperature of water, entering warmer or colder at equipment, as required. The new set temperatures, will allow efficiently operate the system and may increasing the value of T_{out}.

Applying the methodology ANNi (see Fig. 7), the objective function can be minimized to zero to set the optimal input condition which is obtained in Eq. (12), which in this work was resolved by an optimization method from genetic algorithms.

$$Fun(\mathrm{T_{feed}}) = b2 - \sum_{j=1}^{S} W_o(j) - T_{out} + \sum_{j=1}^{S}\left[\frac{2W_o(j)}{1+\exp\left(-2\left(W_i(j,k)\cdot In\left(T_{feed}\right)\right)+\sum_{k=1}^{K}\left(W_i(j,k)\cdot In(k)+b1_{(j)}\right)\right)}\right] \quad (12)$$

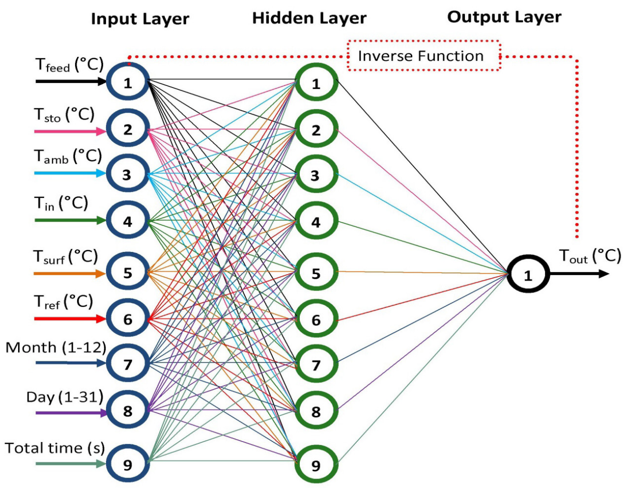

Fig. 7. Architecture of the ANNi for determining the optimum T_{feed} and find the maximum value of T_{out}.

5.1. Adequate value estimate by mean of genetic algorithms

In order to solve the Eq. (12), was used a computational tool called genetic algorithms (GAs). GAs was a stochastic optimization algorithm which employs a population of chromosomes and each of them represents a possible solution. By considering genetic operators, each successive incremental improvement in a chromosome becomes the basis for the next generation. The process continues until the desired number of generations has been completed or the pre-defined fitness value has been reached [20].

This algorithm was programmed to solve and find an unknown value, its purpose was to find the maximum value of the objective function minimized to zero, and thus, from random number the algorithm traces a tendency of behavior between the optimized input values with respect to the value of T_{out}. The efficiency of a GAs was greatly dependent on its tuning parameters; the combinations to control parameters used for running GAs were shown in Table 5.

ANNi model was applied to three experimental tests random used to determine optimal conditions of T_{feed} with respect to a desired value T_{out}, as shown in Table 6. ANNi showed a tendency to which, according to an optimal value T_{feed} a maximum value T_{out} was achieved.

Once resolved the Eq. 12 for the three experimental tests by GAs, we shown in Fig. 8 the maximum value of T_{out} which was in May, reaching a value to the collector output of 49ºC, followed by June with 44.5°C and January with 32.6°C, with entries optimal in the feeding tank of 19°C, 20°C and 13°C, respectively. These conditions predicted by the model ANNi were logical, since in the month of May was where most room temperature occurs in the area and therefore more solar radiation occurs, on the other hand, in January the temperature was lower by the winter. Consequently, in the hot seasons (spring and summer) the value of T_{out} will be high, but in the winter seasons (autumn and winter), the value of T_{out} will be low.

Now, using low temperatures in the feed tank (less than 20°C) demonstrates the ability of PTC to heat water starting from low temperatures.

Table 5
Parameters used for running GAs

Algorithms	Parameters	Value
GAs	Population creation	Random
	Number of generations	100
	Scaling function	Rank
	Selection function	Roulette
	Reproduction crossover probability	0.2
	Mutation function	Uniform
	Mutation rate	0.2
	Crossover function	Scattered

Table 6
Experimental tests to apply the model ANNi-GAs

Inputs	1º Test	2º Test	3º Test
Month	May	June	January
Day	28	20	22
Hour	55193	50400	42648
Temp. input	43.66	40.76	34.06
Temp. ambient	63.43	26.04	39.97
Temp. surface	48.17	46.70	32.06
Temp. reflectance	75.33	69.27	33.51
Temp. feed	Variable to optimize		
Temp. storage	24.35	24.32	19.62
Output			
Temp. output	Find maximum value		

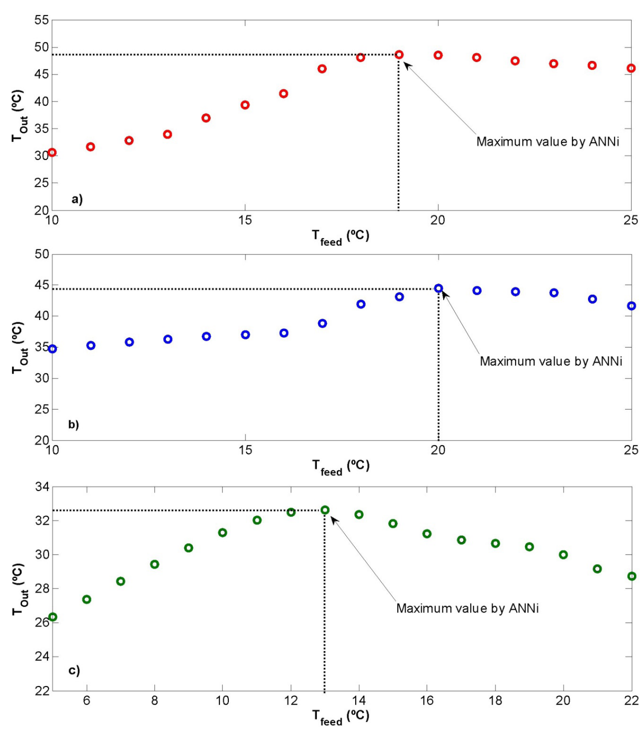

Fig. 8. Optimal conditions from T_{feed} in the PTC with respect to the T_{out} simulated by ANNi, for the month of a) May, b) June and c) January.

Table 7
Comparison between the PTC with respect to other types of collectors

Reference of experimental equipment	Collector type	Advantage	Disadvantage
Kaushika and Reddy [21]	Parabolic dish	High efficiency, with the highest temperature at a single point. Conversion efficiency of steam of 70–80% at 450ºC	The tracking system used is expensive, the total cost of the collector is 38000 Rupees ($ 568.48 USD)
Sobhansarbandi and Atikol [22]	Flat plate (FPC) and Compound parabolic concentrating (CPC)	The outlet fluid temperature of the Flat-Plate collector is between 25–75ºC, whereas for CPC collector this interval is between 25–95ºC. The simulations suggest that a 2 m^2 CPC collector can perform satisfactorily to match the job of 8 m^2 Flat-Plate collectors.	Both equipment are modeled on mathematical equations to simulate winter weather conditions. Both models do not provide an economic analysis of the materials used, which appears to be costly by implementing the use of a controller.
Hsieh [23]	Compound parabolic concentrator (CPC)	Good efficiency (about 56%). Exit temperatures of 50 to 140°C The efficiency curve for the CPC has a far smaller slope than that of a flat-plate collector, which make the CPC particularly suited for high temperature applications	The model does not compare its results obtained with respect to experimental equipment, testing under the conditions of the model. In the model, an economic analysis of the materials is not contemplated, therefore, the equipment could be expensive
Bansal and Uhlemann [24]	Solar collector porous for heating air	Efficiencies up to 60% Long life, which makes it profitable	The performance of the porous collectors is considerably reduced if the pore size is not properly optimized. Back insulation, if not enough, lowers the thermal performance significantly.
Present work	Parabolic trough collector (PTC)	The copper tube turns out to be a very economical material with good conductivity. Total cost is $ 292 USD [10]. The properties of the thermal stainless steel with the mirror polish achieved a better efficiency throughout the day, as it directly affects the increase awareness of the direct and diffuse light. ANNi model was used to optimize input variables according to experimental data of PTC, in order to achieve control the variables of equipment and in turn improve the outlet temperature	By using alternative materials, the outlet temperature was low (with a maximum value of 50ºC). The collector efficiency was low (with collection performance of 37% and better usable thermal energy of 50.5 kW). The ANN model and ANNi are limited to predict and optimize others variables of PTC studied, it is necessary to acquire data from other types of solar collectors to get a general methodology

Finally, in Table 7 provides a comparison between advantages and disadvantages of PTC studied and his simulation-optimization methodology with respect to other types of collectors.

7. Conclusions

A parabolic trough collector with low-cost components was presented as a possible option for use in residential areas, with a good stability during operation and a good characteristic in the materials that allow you to last several years, with a minimum of maintenance.

The PTC was modeled to predict the T_{out} by an ANN model, with a structure of 9 neurons in the input layer, 9 neurons in the hidden layer, and 1 neuron in the output layer. This model was trained with a wide interval of experimental data, using as input variables: the feeding tank temperature (T_{feed}),the storage tank temperature of the water hot (T_{sto}), the water inlet temperature to the solar collector (T_{in}), month (m), day (d), total time (t), ambient temperature (T_{amb}), surface temperature to glass solar collector (T_{surf}) and the temperature of reflector surface (T_{ref}). The results of ANN model showed a good relationship with the experimental data satisfactorily passing significance tests (relationship Fisher F and Student t) and a lower value of RMSE of 0.8055 and 0.57 during training.

Consequently, using the weights and bias from ANN model, a strategy was developed to optimize input variables for increase the value of T_{out}. Once raised the ANNi model, the objective function resulting is resolved by genetic algorithms, showing an increase in T_{out} of 49ºC for May, finding the optimal conditions in the feeding tank temperature of 19ºC, condition suitable for regions where a high ambient temperature was reached.

With this optimized parameter, allow the PTC operates efficiently. To adjust the feed temperature of the tank was necessary to regulate the valve that recirculates water from the storage tank (hot-water) to the feed tank (cold-water).

Finally, this maximum temperature reached by the PTC, using the methodology of ANNi, can satisfy basic needs of residential areas, as with this output temperature of hot water, could be made activities as: take a shower, preheat food, or for pools.

The combinations of computational methods described in this paper were an alternative that allows us to control the process on-line (ANN), and also optimize any of the input variables (ANNi). The GAs application was useful for the search of an unknown value starting from a random population and in turn finds a maximum value.

List of Symbols

In — Input variables
$b1$ — Bia in the input layer
$b2$ — Bia in the output layer
n_s — Output argument of network
W_i — Weights in the input layer
W_o — Weights in the output layer
$x_{i,Norm}$ — Normalized input parameter
$x_{i,real}$ — Experimental input variable
x_{min} — Input variable with the experimental minimum value
x_{max} — Input variable with the experimental maximum value
$RMSE$ — Root Mean Square Error
MAE — Mean Absolute Error
R^2 — Coefficient of determination
P_{sim} — Simulated data of variable T_{out}
P_{exp} — Experimental data of variable T_{out}
P_{exp} — Mean experimental data of variable T_{out}
F — Test Fisher F
T — Test student t
S_x^2 — Variance of the experimental data of variable T_{out}
S_y^2 — Variance of the simulated data of variable T_{out}
$\overline{x}$ — Mean experimental data of variable T_{out}
$\overline{y}$ — Mean simulated data of variable T_{out}
S — Combined standard deviation of the two samples
n_x — Number of experimental data
n_y — Number of simulated data
k — Number of neurons in the input layer
s — Number of neurons in the hidden layer

References

[1] M.S. Hossain, R. Saidura, H. Fayaz, N.A. Rahim, M.R. Islam, J.U. Ahamed, M.M. Rahman, Review on solar water heater collector and thermal energy performance of circulating pipe, Renew. Sust. Energ. Rev., 15 (2011) 3801–3812.

[2] V.K. Jebasingh, G.M.J. Herbert, A review of solar parabolic trough collector, Renew. Sust. Energ. Rev., 54 (2016) 1085–1091.

[3] S.A. Kalogirou, Prediction of flat-plate collector performance parameters using artificial neural networks, Sol. Energy, 80 (2006) 248–259.

[4] A. Sözen, T. Menlik, S. Ünvar, Determination of efficiency of flat-plate solar collectors using neural network approach, Expert Syst. Appl., 35 (2008) 1533–1539.

[5] M. Carner, E. Gedik, A. Keçebas, Investigation on thermal performance calculation of two type solar air collectors using artificial neural network, Expert Syst. Appl., 38 (2011) 1668–1674.

[6] S. Fischer, P. Frey, H. Drück, A comparison between state-of-the-art and neural network modeling of solar collectors, Sol. Energy, 86 (2012) 3268–3277.

[7] M. Laidi, S. Hanini, Optimal solar COP prediction of a solar-assisted adsorption refrigeration system working with activated carbon/metanol as working pairs using direct and inverse artificial neural network, Inter. J. Refrig., 36 (2013) 247–257.

[8] N. Hattab, M. Motelica-Heino, Application of an inverse neural network model for the identification of optimal amendment to reduce copper toxicity in phyto remediated contaminated soils, J. Geochem. Explor., 136 (2014) 14–23.

[9] L.I. Morales, R.A. Conde-Gutiérrez, J.A. Hernández , A. Huicochea, D. Juárez-Romero, J. Siqueiros, Optimization of an absorption heat transformer with two-duplex components using inverse neural network and solved by genetic algorithm, Appl. Therm. Eng., 85 (2015) 322–333.

[10] E. Cardoso, S. Silva-Martinez, A. Alvarez, J.A. Hernández, Design and experimental analysis of low-cost heat water solar collectors, Desal. Wat. Treat., 51(2013) 1302–1309.

[11] E.D. Reyes-Téllez, Estimación de la temperatura de salida en un colector solar de bajo costo, Tesis de maestría, México, 2015, p. 115.

[12] A. Bassam, R.A. Conde-Gutierrez, J. Castillo, G. Laredo, J.A. Hernandez, Direct neural network modeling for separation of linear and branched paraffins by adsorption process for gasoline octane number improvement, Fuel, 124 (2014) 158–167.

[13] C.I. Rocabruno-Valdés, L.F. Ramírez-Verduzco, J.A. Hernández, Artificial neural network models to predict density, dynamic viscosity, and cetane number of biodiesel, Fuel, 147 (2015) 9–17.

[14] M.T. Hagan, M.B. Menhaj, Training feed forward networks with the Marquardt algorithm, IEEE Trans. Neural Netw., 5(6) (1994) 989–993.

[15] M.T. Hagan, H.B. Demuth, M. Beale, editors, Neural network design, Boston, M.A. USA. PWS Publishing Co, 1997.

[16] O. Çelik, A. Teke, H.B. Yıldırım, The optimized artificial neural network model with Levenberge Marquardt algorithm for global solar radiation estimation in Eastern Mediterranean Region of Turkey, J. Clean Prod., 116 (2016) 1–12.

[17] S.P. Verma, Estadística básica para el manejo de datos experimentales: Aplicación en la Geoquímica (Geoquimiometría), Universidad Nacional Autónoma de México, DF México, 2005.

[18] S.P. Verma, Evaluation of polynomial regression models for the Student t and Fisher F critical values, the best interpolation equations from double and triple natural logarithm transformation of degrees of freedom up to 1000, and their applications to quality control in science and engineering, Rev. Mex. Cienc. Geol., 26 (2009) 79–92.

[19] J.A. Hernández, Optimum operating conditions for heat and mass transfer in foodstuffs drying by means of neural network inverse, Food Control, 20 (2009) 435–438.

[20] F.B. Liu, A modified genetic algorithm for solving the inverse heat transfer problem of estimating plan heat source, Inter. J. Heat. Mass Trans., 51 (2008) 3745–3752.

[21] N.D. Kaushika, K.S. Reddy, Performance of a low cost solar paraboloidal dish steam generating system, Energ. Convers. Manage., 41 (2000) 713–726.

[22] S. Sobhansarbandi, U. Atikol, Performance of flat-plate and compound parabolic concentrating solar collectors in underfloor heating systems, J. Sol. Energ., 137 (2015) 034501.

[23] C.K. Hsieh, Thermal analysis of CPC collectors, Sol. Energy, 27 (1981) 19–29.

[24] N.K. Bansal, R. Uhlemann, Development and testing of low cost solar energy collectors for heating air, Sol. Energy, 33 (1984) 197–208.