COMBINATION OF TAGUCHI METHOD AND ARTIFICIAL INTELLIGENCE TECHNIQUES FOR THE OPTIMAL DESIGN OF FLAT-PLATE COLLECTORS

Soteris A. Kalogirou
Cyprus University of Technology,
P. O. Box 50329, 3603, Limassol, Cyprus
e–mail: Soteris.kalogirou@cut.ac.cy

ABSTRACT

In this paper, artificial neural networks (ANNs) and genetic algorithms (GAs) are used for the design of solar flat-plate collectors. It is proved in this paper that by using the Taguchi method for selecting the data required for training the ANN is very effective in allowing the network to learn the behavior of the system satisfactorily. The parameters on which the flat-plate collector design depends are the collector tube material, the type of collector absorbing plate material, the number of collector riser tubes, the collector riser tube diameter, the type of absorber coating and the thickness of the bottom insulating material. By using the method of Taguchi experiments three levels of six variables were used together with three levels of available solar radiation intensity (G_t) and collector inlet minus ambient temperature difference to estimate the collector thermal efficiency. Thus a total of 162 patterns were collected from these combinations from which 130 were used for the training of the ANN and the rest 32, selected randomly, were used to validate the training accuracy. The input parameters are the factors on which the collector performance depends, listed above, and the output parameters are the collector optical efficiency and the loss coefficient. The trained ANN was then used with a genetic algorithm to find the optimum combination of the values of the input parameters, which maximizes the collector efficiency estimated from the optical efficiency and the loss coefficient. The results obtained are very similar to the results achieved by other researchers using much complicated optimization methods, whereas the present method not only is very accurate but it is also very quick.

1. INTRODUCTION

The use of artificial neural networks (ANNs) and genetic algorithms (GAs) for the design of solar collectors is well known [1, 2]. In order to apply this method a number of collector parameters need to be used for the training of the ANN. These parameters must vary for a variety of sizes so as to allow the ANN to learn the behavior of the system well in order to be able to perform predictions with satisfactory accuracy. Subsequently, genetic algorithms are used to obtain the optimum combination of these parameter, which maximize the collector efficiency. In this paper instead of choosing the combination of the actual values of the parameters randomly, these are selected according to the procedures set up by using the Taguchi method. A number of researchers have used genetic algorithms as an optimisation tool for solar energy systems.

Genetic algorithms have been used as a design support tool by Loomans and Visser [3] for the optimization of large hot water systems. The tool calculates the yield and the costs of solar hot water systems based on technical and financial data of the system components. The genetic algorithm allows for the optimization of separate variables as the collector type, the number of collectors, the heat storage capacity and the collector heat exchanger area.

Kalogirou [4] also used genetic algorithms together with a neural network for the optimization of the design of solar energy systems. The method is presented using an example referring to an industrial process heat system. The genetic algorithm is used to determine the optimum values of collector area and the storage tank size of the system which minimize the solar energy price. According to the author the solution reached is more accurate than the traditional trial and error method and the design time is reduced substantially.

Krause *et al.* [5] presented a study in which two solar domestic hot water systems in Germany have been optimized by employing validated TRNSYS models in combination with genetic algorithms. Three different optimization procedures are presented. The first concerns the planning phase while the second concerns the operation of the systems and should be carried out after about one year of data is collected. The third procedure examines the daily performance considering predictions of weather and hot water consumption and actual temperature level in the storage tank.

The objective of the present work is to use a genetic algorithm for the design of a flat-plate collector and for the selection of the right materials for the construction of the collector. The genetic algorithm is used to maximize the thermal efficiency of the collector estimated by the collector optical efficiency and the slope of the standard collector performance curve (heat loss coefficient) by determining the optimum combination of the collector tube material, the type of collector absorbing plate material, the number of collector riser tubes, the collector riser tube diameter, the type of absorber coating and the thickness of the bottom insulating material. For this purpose an evolution strategy based on genetic algorithms is used to determine the optimum solution.

2. ANALYSIS

In this section various relations that are required to determine the useful energy collected and the interaction of the various constructional parameters on the performance of a collector are presented.

The useful energy collected from a collector can be obtained from the following formula [6]:

$$Q_u = AF_R\left[G_t(\tau\alpha) - U_L\left(T_i - T_a\right)\right] \tag{1}$$

where F_R is the heat removal factor given by [6]:

$$F_R = \frac{\dot{m}c_p}{AU_L}\left(1 - \mathrm{Exp}\left[\frac{U_L F' A}{\dot{m}c_p}\right]\right) \tag{2}$$

A physical interpretation of the heat removal factor is that it represents the ratio of the actual useful energy gain that would result if the collector-absorbing surface had been at the local fluid temperature

In Eq. (2) F′ is the collector efficiency factor which is calculated by considering the temperature distribution between two pipes of the collector absorber and by assuming that the temperature gradient in the flow direction is negligible [6]. This analysis can be performed by considering a sheet tube configuration, shown in Fig. 1, where the distance between the tubes is W, the tube diameter is D and the sheet thickness is δ. As the sheet metal is usually made from copper or aluminum which are good conductors of heat, the temperature gradient through the sheet is negligible, therefore the region between the centerline separating the tubes and the tube base can be considered as a classical fin problem. By following this analysis the equation to estimate F′ can be derived [6], given by:

$$F' = \frac{\dfrac{1}{U_L}}{W\left[\dfrac{1}{U_L\left[D + (W - D)F\right]} + \dfrac{1}{C_b} + \dfrac{1}{\pi D_i h_{fi}}\right]} \tag{3}$$

A physical interpretation of F′is that it represents the ratio of the actual useful energy gain to the useful energy gain that would result if the collector absorbing surface had been at the local fluid temperature.

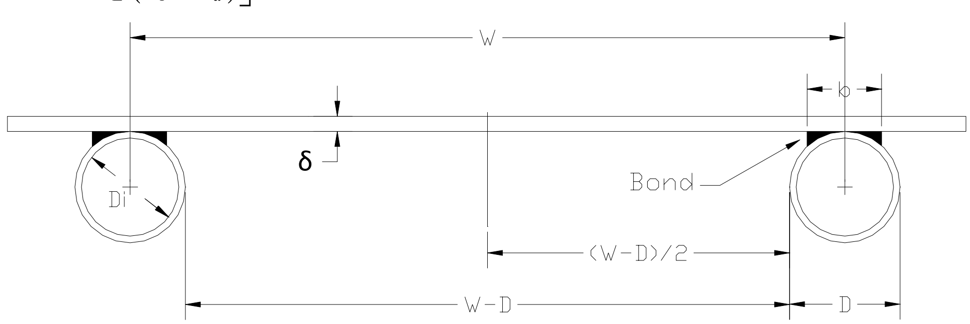

Fig. 1: Flat plate fin and tube configuration.

In Equation (3), C_b is the bond conductance between the riser tube and absorbing plate (see Fig. 1), which can be estimated from knowledge of the bond thermal conductivity, the average bond thickness, and the bond width. The bond conductance can be very important in accurately describing the collector performance and generally it is necessary to have good metal-to-metal contact so that the bond conductance is greater that 30 W/m-K and preferably the tube should be welded to the fin.

Factor F in Eq. (3) is the standard fin efficiency for straight fins with rectangular profile, obtained from:

$$F = \frac{\tanh\left[n(W-D)/2\right]}{n(W-D)/2} \tag{4}$$

where n is given by:

$$n = \sqrt{\frac{U_L}{k\delta}} \tag{5}$$

The collector efficiency factor is essentially a constant factor for any collector design and fluid flow rate. The ratio of U_L to C_b, the ratio of U_L to h_{fi}, and the fin efficiency F are the only variables appearing in Eq. (3) that may be functions of temperature. For most collector designs F is the most important of these variables in determining F′. The factor F′ is a function of U_L and h_{fi}, each of which has some temperature dependence, but it is not a strong function of temperature. Additionally, the collector efficiency factor decreases with increased tube center-to-center distances and increases with an increase in both material thicknesses and thermal conductivity. Increasing the overall loss coefficient, U_L, decreases F′ while increasing the fluid-tube heat transfer coefficient, h_{fi}, increases F′.

Therefore it is obvious from the analysis presented above that by increasing F′ more energy can be intercepted by the collector. By keeping all other factors constant an increase of F′ can be obtained by decreasing W. However, decrease in W means increased number of tubes and therefore extra cost would be required for the construction of the collector.

The collector efficiency is found by dividing Q_u by the incident radiation AG_t. By doing so the following Equation is obtained:

$$\eta = F_R(\tau\alpha) - F_R U_L\left[\frac{T_i - T_a}{G_t}\right] \tag{6}$$

By plotting η against $\Delta T/G_t$ a straight line is obtained with the slope equal to $F_R U_L$, called the loss coefficient and the intercept on the y-axis, equal to $F_R(\tau\alpha)$, called optical efficiency.

3. METHOD DESCRIPTION

As can be understood from the above analysis the parameters on which the flat-plate collector design depends are the collector tube material, the type of collector absorbing plate material, the number of collector riser tubes, the collector riser tube diameter, the type of absorber coating and the thickness of the bottom insulating material, which affects the heat losses from the back of the collector. The magnitude of the parameters applied in this work is shown in Table 1 in three levels except collector tube material for which two levels are used. Each of these levels carries a number of characteristics as the thermal conductivity for the materials and optical properties for the absorber coatings.

The collector performance depends also on the solar radiation intensity and the temperature difference between the collector inlet and ambient temperature. For these parameters again three levels of data were used as shown in Table 2.

When a full-functional orthogonal array is considered with the data shown in Tables 1 and 2, a total of 2^1x3^7 (4374) experiments are required to cover all possible combinations. By using the method of Taguchi experiments however, only 18 experiments are required as shown in Table 3.

Thus by applying this method, a total of 162 patterns were collected from the combinations shown in Table 3. i.e., for each row of the vertical columns (18 data) they were 9 combinations of the horizontal data of radiation and temperature (18x9=162). All estimations were performed using CoDePro (collector design program) software. The actual data used here were obtained from Ref. [7]. From these patterns, 130 were used for the training of the ANN and the rest 32, selected randomly, were used to validate the training accuracy. The input parameters are the factors on which the collector performance depends, listed in Tables 1 and 2, and the output parameters are the collector optical efficiency, $F_R(\tau\alpha)$ (intercept on the y-axis of the collector performance curve) and the loss coefficient, $F_R U_L$ (slope of the collector performance curve). A sample of the training data set is shown in Table 4.

ANN models represent a new method in system prediction. An ANN operates like a “black box” model, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data, similar to the way in which a non-linear regression might perform. [8].

TABLE 1: PARAMETERS ON WHICH THE FLAT-PLATE COLLECTOR PERFORMANCE DEPEND

Parameter	Level 1	Level 2	Level 3
A. Collector tube material	Copper	Stainless steel	-
B. Collector absorbing plate material	Aluminum	Copper	Stainless steel
C. Number of collector riser tubes	8	11	14
D. Collector riser tube diameter	3	4	5
E. Type of absorber coating	Tinox	Vacuum spattering	Spray painting
F. Thickness of bottom insulation	2.5	3.8	5

TABLE 2: COLLECTOR OPERATING CONDITIONS

Parameter	Level 1	Level 2	Level 3
P. Solar radiation intensity (W/m^2)	800	900	1000
Q. Temperature [$=T_i-T_a$] (°C)	10	20	30

TABLE 3: EXPERIMENTAL FACTORS OF THE COLLECTOR AS OBTAINED BY THE TAGUCHI METHOD

						P	1	1	1	2	2	2	3	3	3
						Q	1	2	3	1	2	3	1	2	3
No.	A	B	C	D	E	F	1	2	3	4	5	6	7	8	9
1	1	1	1	1	1	1									
2	1	1	2	2	2	2									
3	1	1	3	3	3	3									
4	1	2	1	1	2	2									
5	1	2	2	2	3	3									
6	1	2	3	3	1	1									
7	1	3	1	2	1	3									
8	1	3	2	3	2	1									
9	1	3	3	1	3	2									
10	2	1	1	3	3	2									
11	2	1	2	1	1	3									
12	2	1	3	2	2	1									
13	2	2	1	2	3	1									
14	2	2	2	3	1	2									
15	2	2	3	1	2	3									
16	2	3	1	3	2	3									
17	2	3	2	1	3	1									
18	2	3	3	2	1	2									

The numbers in the various parameters represent the level of the parameter according to Tables 1 and 2.

TABLE 4: A SAMPLE OF THE TRAINING DATA SET

Input parameters								Output parameters	
A	B	C	D	E	F	P	Q	$F_R(\tau\alpha)$	F_RU_L
1	1	8	3	1	2.5	800	10	0.7584	4.679
1	1	8	3	1	2.5	800	20	0.7586	4.658
1	1	8	3	1	2.5	800	30	0.7595	4.636
1	1	8	3	1	2.5	900	10	0.7578	4.677
1	1	8	3	1	2.5	900	20	0.7581	4.660
1	1	8	3	1	2.5	900	30	0.7589	4.638
1	1	8	3	1	2.5	1000	10	0.7572	4.678
1	1	8	3	1	2.5	1000	20	0.7576	4.661
1	1	8	3	1	2.5	1000	30	0.7383	4.639
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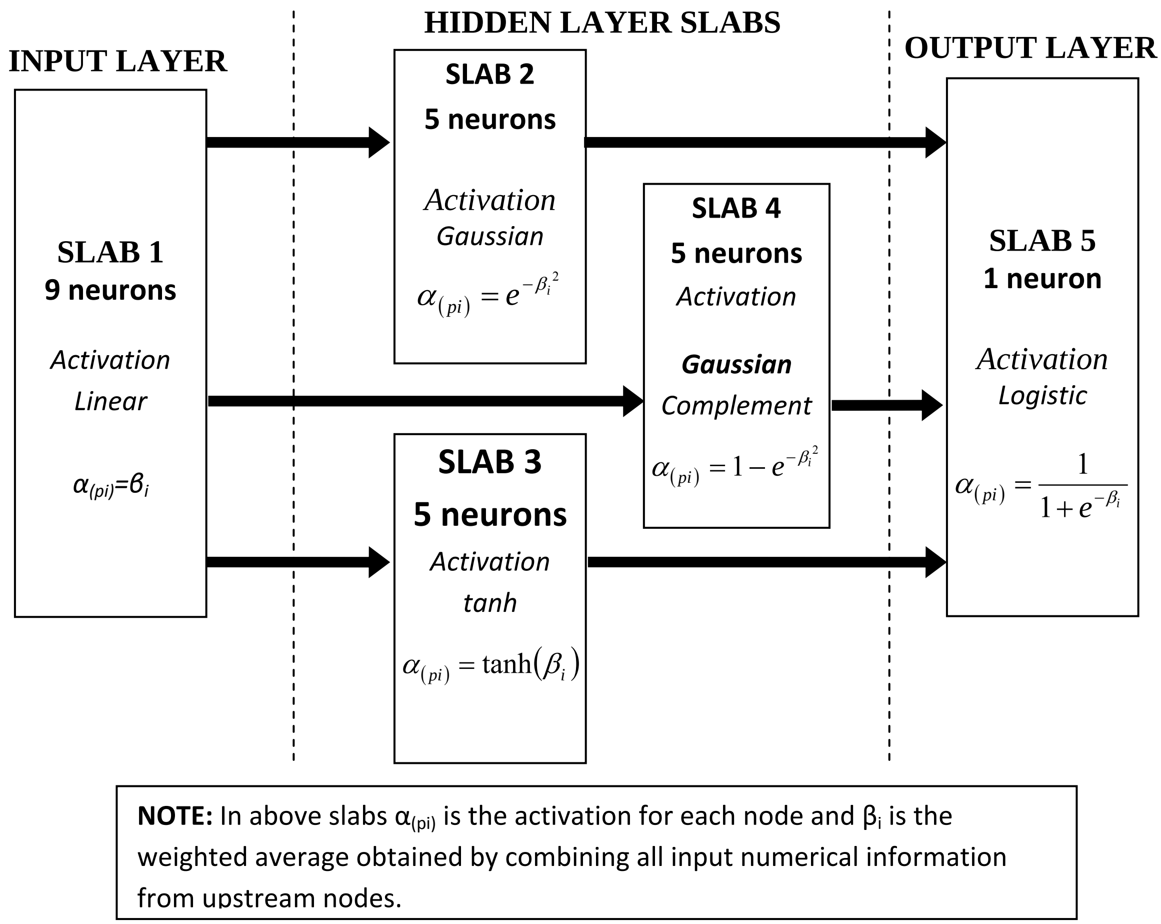

Fig. 2: The employed neural network architecture.

Various network architectures have been investigated to find the one that could provide the best overall performance. The architecture, among those tested, that gave the best results and was adopted for the present work, is a multilayer back-propagation ANN, shown in Fig. 2. This architecture has been used in a number of engineering problems for modeling and prediction, with very good results, and it is a feedforward architecture composed of five slabs, three of which are hidden [8]. There are different activation functions in each slab so as to detect different featureds in a pattern processed through the network. Eight element inputs have been used corresponding to the values of the input parameters listed above. The learning procedure was implemented by using the back-propagation algorithm. The learning rate was set to a constant value of 0.1 and the momentum factor to 0.3. The weights were initialized to a value of 0.3. The back-propagation learning algorithm and the architecture employed are described in [9].

It should be noted that as shown in Table 4 numbers are used to differentiate the different inputs for parameters A, B, D and E, whereas for the other parameters actual input data were used. The training was performed with a satisfactory accuracy with correlation coefficients equal to 0.9914 and 0.9886 for the two parameters respectively, which are very satisfactory as they are very close to unity. The results also show that 94% of the data are within 5% error, which is also very satisfactory. As this accuracy is based to a large extent on the data used to train the ANN, the selection of the training data with the Taguchi method seems to be very effective.

4. GENETIC ALGORITHM

The genetic algorithm (GA) is a model of machine learning, which derives its behavior from a representation of the processes of evolution in nature. This is done by the creation within a machine/computer of a population of individuals represented by chromosomes. Essentially these are a set of character strings that are analogous to the chromosomes that we see in the DNA of human beings. The individuals in the population then go through a process of evolution.

In an over simplified consideration, at the molecular level what happens is that a pair of chromosomes bump into one another, exchange chunks of genetic information and drift apart. This is the recombination operation, which in GAs is generally referred to as crossover because of the way that genetic material crosses over from one chromosome to another.

The crossover operation happens in an environment where the selection of who gets to mate is a function of the fitness of the individual, i.e. how good the individual is at competing in its environment. Some GAs use a simple function of the fitness measure to select individuals (probabilistically) to undergo genetic operations such as crossover or asexual reproduction, i.e., the propagation of genetic material remains unaltered. This is fitness - proportionate selection. Other implementations use a model in which certain randomly selected individuals in a subgroup compete and the fittest is selected. This is called tournament selection. The two processes that most contribute to evolution are crossover and fitness based selection/reproduction. Mutation also plays a role in this process.

GAs are used for a number of different application areas. An example of this would be multidimensional optimization problems in which the character string of the chromosome can be used to encode the values for the different parameters being optimized. In practice, therefore, this genetic model of computation can be implemented by having arrays of bits or characters to represent the chromosomes. Simple bit manipulation operations allow the implementation of crossover, mutation and other operations.

When the GA is executed, it is usually done in a manner that involves the following cycle [10]. Evaluate the fitness of all of the individuals in the population. Create a new population by performing operations such as crossover, fitness-proportionate reproduction and mutation on the individuals whose fitness has just been measured. Discard the old population and iterate using the new population. One iteration of this loop is referred to as a generation. More details on genetic algorithms can be found in Goldberg [11].

Genetic algorithms (GA) are suitable for finding the optimum solution in problems were a fitness function is present. Genetic algorithms use a “fitness” measure to determine which of the individuals in the population survive and reproduce. Thus, survival of the fittest causes good solutions to progress. A genetic algorithm works by selective breeding of a population of “individuals”, each of which could be a potential solution to the problem. The genetic algorithm is seeking to breed an individual, which either maximizes, minimizes or it is focused on a particular solution of a problem. In this case, the genetic algorithm is seeking to breed an individual that maximizes the collector efficiency.

The larger the breeding pool size, the greater the potential of it producing a better individual. However, the fitness value produced by every individual must be compared with all other fitness values of all the other individuals on every reproductive cycle, so larger breeding pools take longer time. After testing all of the individuals in the pool, a new “generation” of individuals is produced.

During the setting up of the GA the user has to specify the adjustable chromosomes, i.e. the parameters that would be modified during evolution to obtain the maximum or minimum values of the fitness functions. In this work, the fitness function used was the collector efficiency. Additionally the user has to specify the range of the input parameters called constraints.

The genetic algorithm parameters used in the present work are:

- Population size=50

Population size is the size of the genetic breeding pool, i.e., the number of individuals contained in the pool. If this parameter is set to a small value, there would not be enough different kinds of individuals to solve the problem satisfactorily. On the other hand, if there are too many in the population, a good solution will take longer to be found because the fitness function must be calculated for every individual in every generation.

- Crossover rate=90%

Crossover rate determines the probability that the crossover operator will be applied to a particular chromosome during a generation.

- Mutation rate=1%

Mutation rate determines the probability that the mutation operator will be applied to a particular chromosome during a generation.

- Generation gap=96%

Generation gap determines the fraction of those individuals that do not go into the next generation. It is sometimes desirable that individuals in the population be allowed to go into next generation. This is especially important if individuals selected are the most fit ones in the population.

- Chromosome type=continuous

Populations are composed of individuals, and individuals are composed of chromosomes, which are equivalent to variables. Chromosomes are composed of smaller units called genes. There are two types of chromosomes, continuous and enumerated. Continuous are implemented in the computer as binary bits. The two distinct values of a gene, 0 and 1, are called alleles. Multiple chromosomes make up the individual. Each partition is one chromosome, each binary bit is a gene, and the value of each bit (e.g., 1, 0, 0, 1, 1, 0) is an allele. Enumerated chromosomes consist of genes, which can have more allele values than just 0 and 1. There are two different types of enumerated chromosomes; 'repeating genes' and 'unique genes'. Unique genes have to be used in cases that each gene is used only once and repeating genes where chromosomes can have repeating genes.

The genetic algorithm is usually stopped after the best fitness remained unchanged for a number of generations or when the optimum solution is reached. In this work the genetic algorithm was stopped after the best fitness remained unchanged for 75 generations.

5. RESULTS

The input parameters (adjustable chromosomes) were used in combination with a genetic algorithm program to find the values that maximize collector efficiency, estimated from the collector optical efficiency and the collector loss coefficient. These parameters were constrained to move within the values shown in Tables 1 and 2. The whole model was set – up in a spreadsheet program in which the various parameters are entered into different cells. The estimated values of collector optical efficiency (intercept on the y-axis of the collector performance curve [=$F_R(\tau\alpha)$]) and loss coefficient (slope of the collector performance curve [= F_RU_L]) were used in Eq. (6) to estimate the collector efficiency which is the fitness function that needs to be maximized.

The optimum combination of parameters obtained from the GA are shown in Table 5.

TABLE 5: OPTIMUM COMBINATION OF PARAMETERS OBTAINED FROM THE GA

Parameter	Value
A. Collector tube material	Copper
B. Collector absorbing plate material	Copper
C. Number of collector riser tubes	11
D. Collector riser tube diameter	9mm
E. Type of absorber coating	Tinox
F. Thickness of bottom insulation	50mm

These parameters result in an optimum efficiency that depends on the magnitude of the solar radiation available. For the three values of solar radiation considered the results shown in Table 6 are obtained. It should be noted that for each run of the program the optimum solution was reached in less than 5 seconds on a Pentium 3.2 GHz machine, which is very fast.

TABLE 6: COLLECTOR EFFICIENCY AT VARIOUS VALUES OF SOLAR RADIATION

Solar radiation (W/m^2)	Efficiency
800	0.7536
900	0.7581
1000	0.7614

6. CONCLUSIONS

It is proved that this way of selecting the variety of training parameters with the Taguchi method is very effective in allowing the ANN to learn the behavior of the system satisfactorily.

To find the optimum parameters a genetic algorithm is used. The results showed that the optimum parameters are copper for the collector riser tube and absorbing plate material, 11 riser tubes, 9 mm riser tube diameter, Tinox absorber coating and 50 mm bottom insulating material. The results obtained are very similar to the results obtained by other researchers using much complicated optimization methods, like the grey relational analysis, whereas the present method not only is very accurate but it is also very quick.

7. NOMENCLATURE

A	Collector area, m^2
c_p	Specific heat capacity, J/kg-K
D	Riser tube outside diameter, m
D_i	Riser tube inside diameter, m
F'	Collector efficiency factor
F	Fin efficiency
F_R	Heat removal factor
G_t	Solar radiation, W/m^2
h_{fi}	Heat transfer coefficient inside absorber tube, W/m^2-K
k	Absorber thermal conductivity, W/m-K
m	Mass flow rate, kg/s
N	Number of riser tubes
Q_u	Rate of useful energy collected, W
T_a	Ambient temperature, K
T_i	Collector inlet temperature, K
U_L	Overall heat loss coefficient, W/m^2-K
W	Distance between riser tubes, m

Greek

δ	Absorber (fin) thickness, m
ΔT	Temperature difference [=T_i-T_a], K
$\tau\alpha$	Transmittance-absorptance product

8. REFERENCES

[1] Kalogirou S.A., 2003. Use of genetic algorithms for the optimal design of flat plate solar collectors, *Proceedings of the ISES 2003 Solar World Congress on CD-ROM*, Goteborg, Sweden.

[2] Kalogirou S.A., 2006. Artificial neural networks and genetic algorithms for the optimisation of solar thermal systems**,** *Proceedings of the IX World Renewable Energy Congress on CD-ROM*, Florence, Italy.

[3] Loomans M., Visser H., 2002. Application of the genetic algorithm for the optimisation of large solar hot water systems, *Solar Energy*, Vol. 72, pp. 427-439.

[4] Kalogirou S.A., 2002. Use of artificial intelligence for the optimisation of solar systems, *International Journal of Renewable Energy Engineering*, Vol. 4, pp. 499-505.

[5] Krause M., Valen K., Wiese F., Ackermann H., 2002. Investigations on optimizing large solar thermal systems, *Solar Energy*, Vol. 73, pp. 217-225.

[6] Kalogirou S.A., 2009. *Solar energy engineering: Processes and systems*, ISBN: 978-0-12-374501-9, Academic Press, Elsevier Science.

[7] Kuo C.-F. J., Su T.-L., Jhang P.-R., Huang C.-Y., Chiu C.-H., 2011. Using the Taguchi method and grey relational analysis to optimize the flat-plate collector process with multiple quality characteristics in solar energy collector manufacturing, *Energy*, Vol. 36, pp. 3554-3562.

[8] Kalogirou S.A., 2000.Applications of artificial neural networks for energy systems, Special Issue of *Applied Energy,* Vol. 67, No. 1-2, pp. 17-35.

[9] Kalogirou S.A., Panteliou A.D., Dentsoras, A., 1999. Modelling of solar domestic water heating systems using artificial neural networks. *Solar Energy,* Vol. 65, No. 6, pp. 335-342.

[10] Zalzala A. and Fleming P. (1997) Genetic algorithms in engineering systems, *The Institution of Electrical Engineers*, London, UK.

[11] Goldberg D. E. (1989) *Genetic Algorithms in Search Optimisation and Machine Learning*, Addison-Wesley, Reading, MA.