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Purpose of neuronal method for modeling of solar collector

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Abstract
Artificial Neural Networks (ANN) are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems. They have been used in diverse applications and have shown to be particularly effective in system identification and modeling as they are fault tolerant and can learn from examples. On the other hand, ANN are able to deal with non-linear problems and once trained can perform prediction at high speed. The objective of this work is the characterization of the integrated collector-storage solar water heater (ICSSWH) by the determination of the day time thermal (and optical) properties, and Night time heat loss coefficient with experimental temperatures, and predictive temperatures by (ANN). Because of that, an ANN has been trained using data for three types of systems, all employing the same collector panel under varying weather conditions. In this way the network was trained to accept and handle a number of unusual cases. The data presented as input were, the working systems (day or night), the type of system, the year, the month, the day, the time, the ambient air temperature, and the solar radiation. The network output is the temperature of the four tanks of storage unit. The correlations coefficients (R^2 –value) obtained for the training data set was equal to 0.997, 0.998, 0.998, and 0.996 for the four temperatures of each tank. The results obtained in this work indicate that the proposed method can successfully be used for the characterization of the ICSSWH.

Keywords: ICSSWH; Artificial Neural Networks; Characterization; Reflector-insulator.

1. Introduction

Nowadays, the use of solar energy is classified as an important issue on the agenda of scientists as part of the general trend of developing new renewable and environmental friendly energies that face the shortage and fluctuating prices of conventional energies and to avoid their negative environmental effects like depletion of the ozone layer, greenhouse effects, global heating, etc. Recognizing the importance of such concerns, Algeria with its location and high solar energy potentials (yearly average solar radiation is about 2000 kW h/m2 year, [1] is now paying more effort and attention in an attempt to unravel the strands of the above stated issues. Solar energy collectors are a special kind of heat exchangers that transform solar radiation energy to internal energy of the transport medium, [2]. The major component of the solar system being considered here is the flat plate solar collector. This device absorbs the incoming solar radiation and converts it into heat and also transfers this heat to a fluid flowing through the collector, [3]. A major performance difference between solar water heaters which employ separate components for heating and storage, and those which integrate these two functions into a single unit is their night time heat loss properties. The solar water heater under study is basically a 'flat-plate' solar collector, of aperture area 0.994 m^2, with a built-in storage capacity of 60 l. Because of the large thermal mass of such body of water, the system can never achieve thermodynamic steady state conditions and hence, standard test methods for flat plate solar collectors are inapplicable ([4], [5]), and a major simplification was that the temperature in the collector was considered to be uniform. This assumption is not far from the truth, because of that, this study proposes ANN model to predict the temperatures of the storage unit. In order to help quantify the problem, we propose an integrated collector-storage water heater composed of four tanks and equipped with a specially designed flap reflector (Figure 1). This latter makes it possible to concentrate solar radiation on the glazed surface when disposed to the radiation, and can be used as an insulating top cover in order to reduce nighttime's thermal losses when folded back. Then a comparison between experimental and neuronal study is carried out for the purpose of enabling us to determine the optical and thermal performances of this new prototype and to evaluate the gains brought by the flap reflector-insulator.

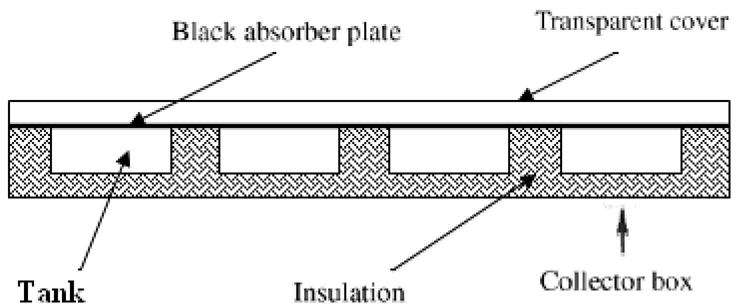

Figure 1. Experimental setup

The studied three variants in this work are collector with reflector and insulator at night during the period of October 16-Novembre 16, 2002, collector with reflector and without insulator at night during the period of November 19-December 28, 2002, and collector without reflector and without insulator at night during the period of December 30, 2002 - March 8, 2003. The experimental data (time, the four temperatures of tanks, the air ambient temperature, and the solar radiation, are collected for every 5 minutes for both day (unit heating) and night (unit cooling) and then separated into two files for the training and the validation of the ANN. The first file includes 19712 data points, while the validation ones comprises 9863 data points. It should be noted that every testing of the ICSSWH unit was performed without draw-off.

2. Artificial neural network model

The use of ANNs has grown in popularly during the last few years. The reason for this is that neural networks represent a novel and modern approach that can provide solutions to problems for which conventional mathematics, algorithms and methodologies are unable to find a satisfactory and acceptable solution. These problems are usually very complex and some of the mechanisms involved have not been fully understood by the researchers dealing with them.

ANNs are inspired by the human brain functionality and structure, which can be imagined as a network that comprises of densely interconnected elements called neurons. Despite this fact the ANNs' objective is not to model it. Instead, their purpose is to be useful models that can be used for problem solving and knowledge engineering, in a way that resembles the human process for problem solving and knowledge acquisition. Both biological and artificial networks have the following main and important features: learning adaptation, generalization, massive parallelism, robustness, associative storage information and spatiotemporal information processing, [6].

The operational manner of ANNs is that when inputs are applied to the input neurons the network performs a summation of the weighing factors and then it activates one or more specific output neurons that are capable of providing the most suitable answer for the given problem.

By trainings the neural network, can be built into it, [7]. The training of a supervised neural network occurs by presenting typical input patterns and the corresponding expected output patterns. The strength or otherwise the weights of the connections between the neurons are modified by using an error measurement between the actual and the expected results, until the results of the network are satisfactory. For this procedure a backpropagation algorithm is used. It propagates the error, between the expected and actual results, backwards through the structure of the network and then it computes the weight modifications necessary to improve the actual results of the network's outputs in order to provide the most correct solution to the problem.

Multilayer perceptron is the most popular neural network. A multilayer perceptron is a feed forward network, which can perform static mapping between input space and an output space. It consists of neurons organized in a number of layers that can be categorized into three parts. The first part is the input layer that allows that network to communicate with the environment, the second part is commonly known as the hidden part, where one, two or more layers of neurons exist depending on the problem's demands and generalization requirements.

Several authors have reported application of ANN for estimation of the performance of solar systems. A ANN model for estimation of performance of a thermosiphon solar water heater has been reported by Kalogirou et al., (1999), [8]. Kalogirou (2004b), [3] has used ANN model and genetic algorithms for the optimization of solar systems. ANN has also been used for prediction of flat-plate collector performance parameters by Kalogirou (2006), [9]. Sözen et al., (2007), [10] have used ANN model for determination of efficiency of flat-plate solar collectors. Kalogirou et al. (2008), [11] have developed a neural network-based fault diagnostic system for solar thermal applications.

In this work the application of ANN modeling of the four temperatures was performed using MATLAB®. The system has four layers which are input layer; two hidden layers, and an output layer. The input layer consists of all the input factors that are processed in the course of two hidden layers. Finally the generated output vector is computed in the output layer.

The structure of the optimized ANN model is presented in the Table 1. Selected ANN architecture is depicted in Figure 2. The performance of the neural network model for the first temperature (T_1) and fourth temperature (T_4) is shown in Figures 3 and 4. The correlation coefficients of the four temperatures are 0.997, 0.998, 0.998, and 0.996 respectively.

Table 1. Structure of the optimized artificial neural networks model

Type of network	FFBP NN	
Layer	No. of neurons	Activation function
Input layer	8	
First hidden layer	18	Hyperbolic tangent sigmoid
Second hidden layer	18	Hyperbolic tangent sigmoid
Output layer	4	Linear
Training Algorithm	BRBP using Levenberg–Marquardt optimization	

3. Experimental and neuronal characterization

In this part, we have adopted the MUE *'maximum useful efficiency'* formalism, developed by, [4] for the determination of the day time thermal (and optical) proprieties of this integrated collector storage with experimental and predicted temperatures. The MUE of such a system can be cast in a mathematical form which is similar to the familiar Hottel–Whillier–Bliss equation, [12] for a low-mass flat-plate collector, but where the variables take on time averaged values, specifically [5], In Eq.

$$\eta = \overline{K} F_E \eta_o - \frac{F_E U_L \left(\overline{T_f} - \overline{T}_a\right)}{\overline{I}} \tag{1}$$

In Eq. (1), T is the temperature of the water in storage, T_a is the ambient temperature and I is the irradiance on the aperture plane of the collector. η_o is the optical efficiency and U the heat loss coefficient of the collector–storage unit. K is the incidence angle modifier and F_E is an enthalpy retrieval factor defined as:

$$F_E = \frac{M_w C_w}{M_w C_w + M_{cs} C_{cs}} \tag{2}$$

where M_w and C_w are, respectively, the mass and heat capacity of the water and M_{cs} and C_{cs} are the respective mass and heat capacity of the material from which the collector–storage unit is fabricated. Most important of all, the bars indicate time average over the daily heating period, from sunrise until the time the water reaches its maximum daily temperature. That is to say, we use *daily average*, rather than instantaneous, values of the variables in Eq. (1). The bar over K indicates a daily energy average, which is fairly constant on a monthly basis, [5]. MUE is defined as:

$$\eta = \frac{M_w C_w \left(T_{\max} - T_{sunrise}\right)}{A_c \int I(t) dt} \tag{3}$$

where A_c is the collector aperture area, and the integral is taken over the time from sunrise until the water reaches its maximum temperature.

We remark that, in contrast to a semi-empirical test method that was subsequently developed for testing integrated collector–storage systems, [13,14], the MUE method is *not empirical*, and in that all of its parameters have a clear physics-based interpretation. It follows directly the fundamental heat flow equation, as a consequence of the long relaxation time of the system, [5].

The results obtained by the application of the Eq. 1 are presented in Figure 5 and Figure 6. The table 2 presents all proprieties (thermal and optical) for two systems. The comparison between results obtained from the two systems, show the improvement of efficiency when we use the reflector for the two cases (experimental and neuronal).

In order to compute the night time heat loss coefficient, we use data between sunset and sunrise of the next day. For each 5 minutes, we calculate the difference between the mean water temperature and ambient, then averaging the results over $\Delta t = t_{sunrise} - t_{sunset}$. This average, $(T_f - T_a)$ was then divided into the temperature difference, $(T_i - T_f)$, between the water's initial temperature and final temperature during this time. The heat loss coefficient can be calculated as follow,[4]:

$$U_L = \frac{\left(M_w C_w + M_{cs} C_{cs}\right)\left(T_i - T_f\right)}{A \Delta t \left(T_f - T_a\right)} \tag{4}$$

The Table 2 summarized results of the heat loss coefficient of systems obtained by the variation of internal energy with $\left(\overline{T_f} - \overline{T_a}\right)$. It can be clearly seen that the value of heat loss coefficient for collector without insulator is almost double the one for collector with insulator in the tow case (experimental and neuronal). These results show the importance of the insulator at night.

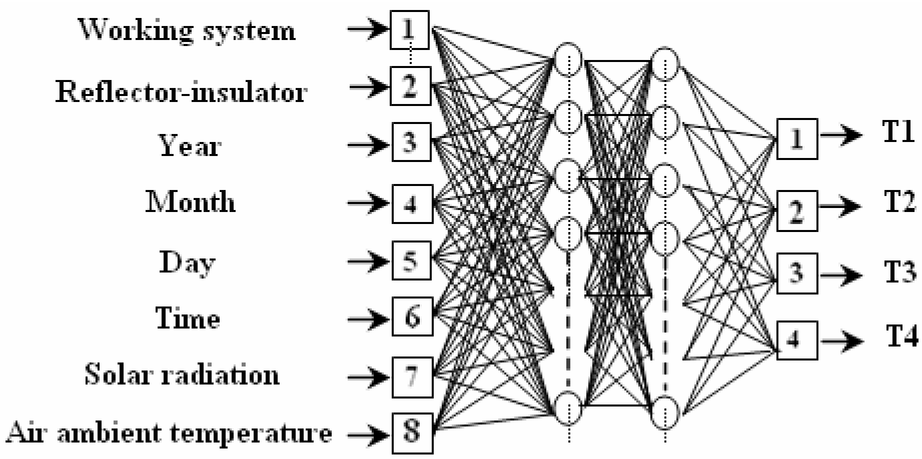

Figure 2. Multi-layer feedforward neural network for the prediction of the four temperatures of tanks.

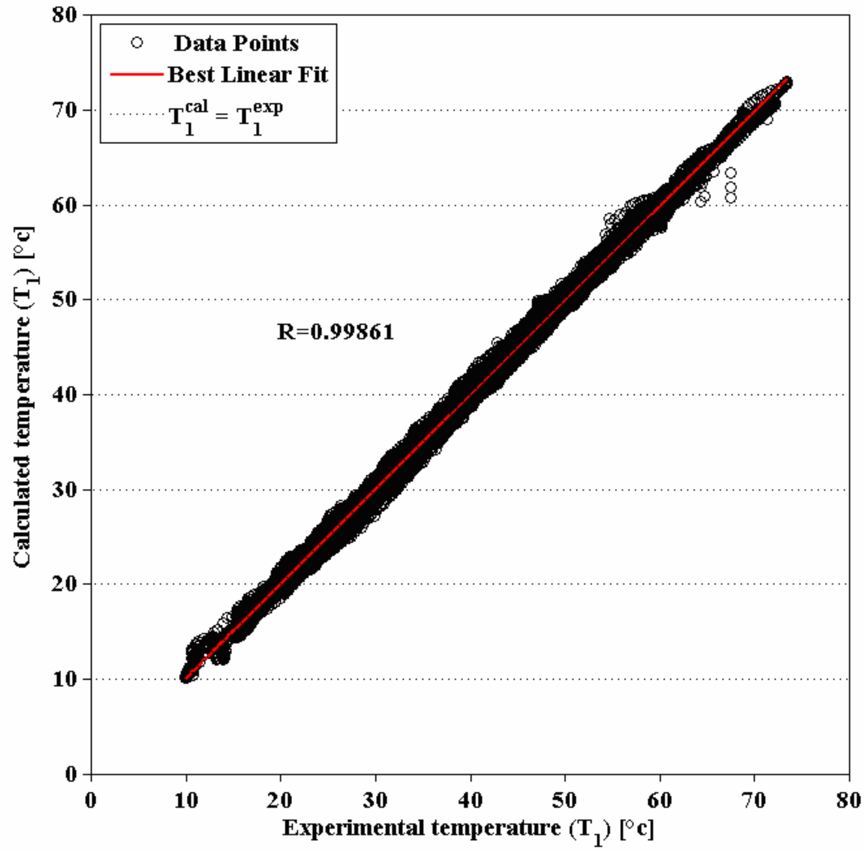

Figure 3. Performance of ANN to calculate the first temperature (T_1).

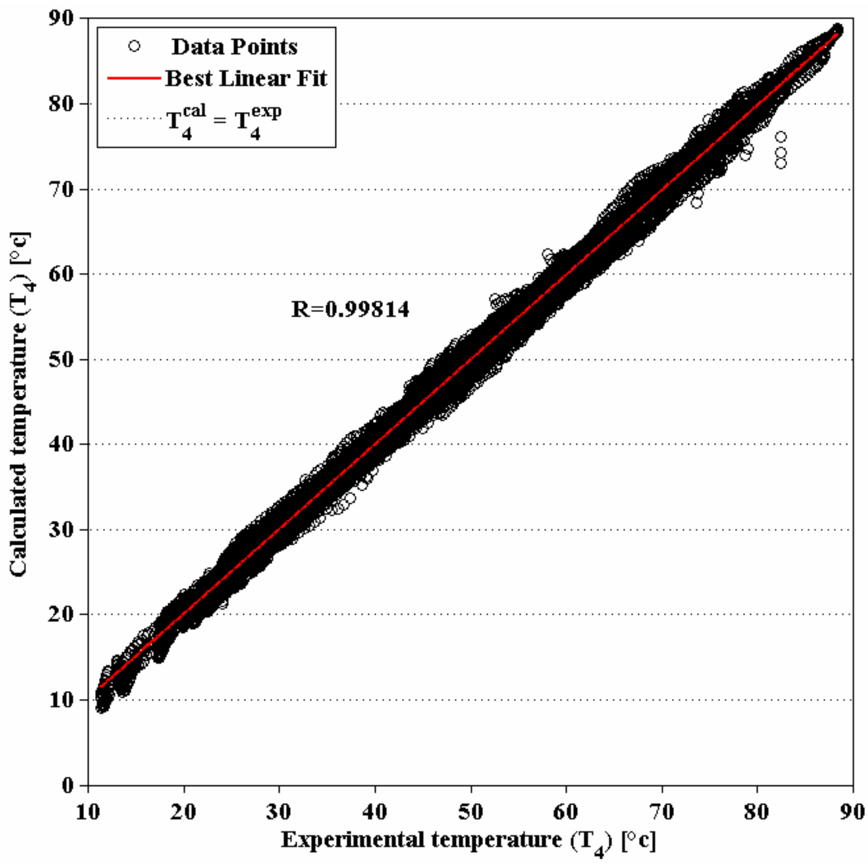

Figure 4. Performance of ANN to calculate the first temperature (T_4).

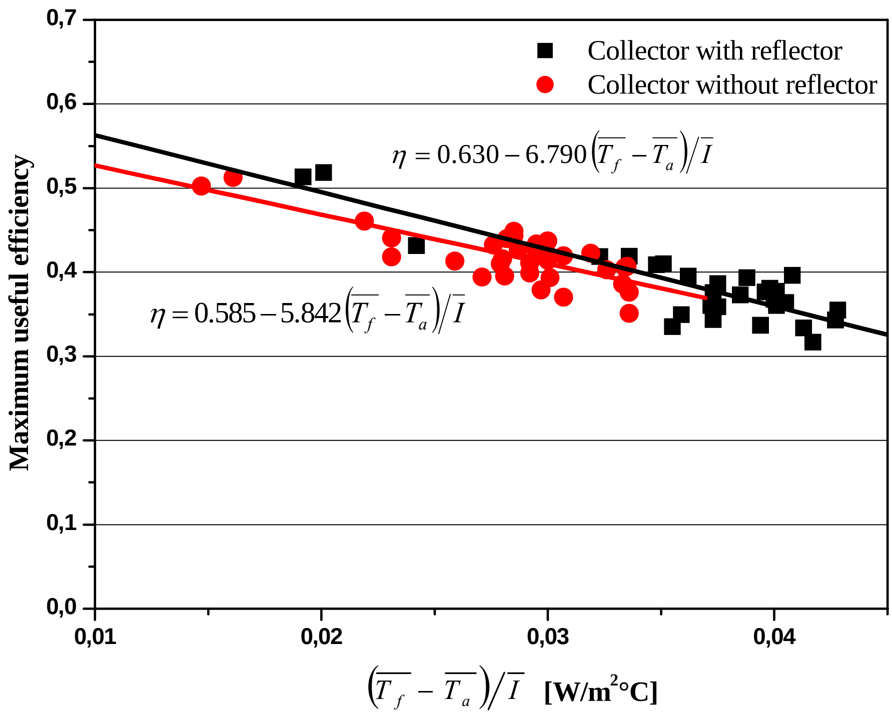

Figure 5. Characteristic graph of ICSSWH using experimental temperatures (collector with reflector /collector without reflector).

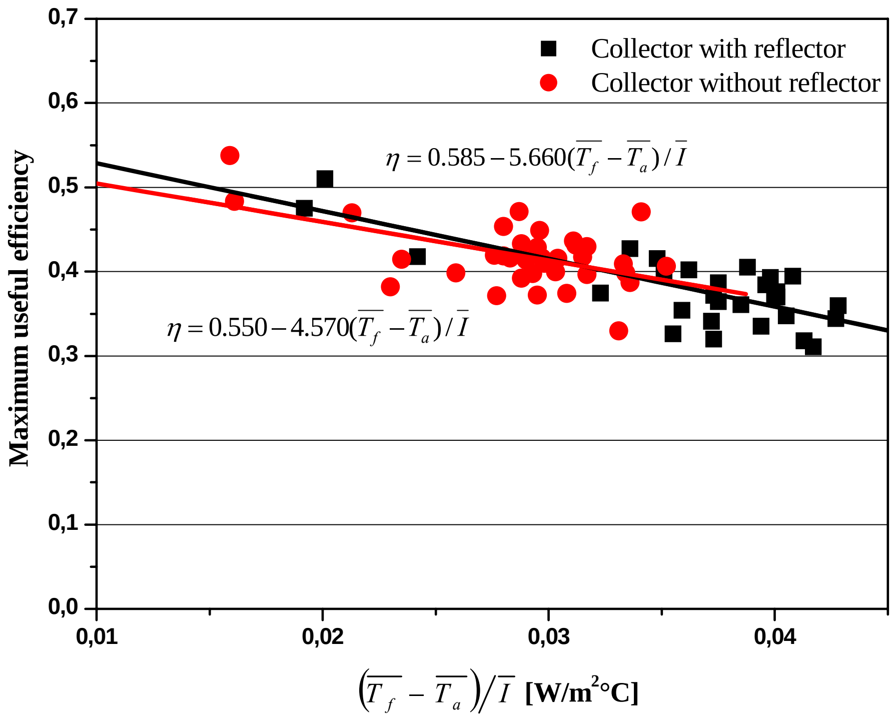

Figure 6. Characteristic graph of ICSSWH using predicted temperatures ANN model (collector with reflector /collector without reflector)

Table 2. Day and night time thermal (and optical) properties of integrated collector–storage unit.

Test	**Period**	**MUE equation**	
		Experimental temperatures	**Predicted temperatures**
ICSSWH **With reflector and insulator**	**16/10/02 - 16/11/02**	$\eta = 0.63056 - 6.77869(\overline{T_f} - T_a)/\overline{I}$ $\overline{K}F_E\eta_0 = 0.63056$ **-F_EU_L**=-6.77869 (W/m^2°C), **F_E**=0.979 **U_L** =6.924 (W/m^2°C)	$\eta = 0.58505 - 5.66048(\overline{T_f} - T_a)/\overline{I}$ $\overline{K}F_E\eta_0 = 0.58505$ **-F_EU_L**=-5.66048 (W/m^2°C), **F_E**=0.979, **U_L** =5.782 (W/m^2°C)
ICSSWH **Without reflector and without insulator**	**30/12/02 - 08/02/03**	$\eta = 0.58531 - 5.84233(\overline{T_f} - T_a)/\overline{I}$ $\overline{K}F_E\eta_0 = 0.58531$ **-F_EU_L**=-5.84233 (W/m^2°C), **F_E**=0.979 **U_L** =5.967 (W/m^2°C)	$\eta = 0.55044 - 4.5705(\overline{T_f} - T_a)/\overline{I}$ $\overline{K}F_E\eta_0 = 0.55044$ **-F_EU_L**=-4.5705 (W/m^2°C) **F_E**=0.979**,** **U_L** =4.668 (W/m^2°C)
Equation of the storage internal energy			
ICSSWH **With reflector and insulator**	**16/10/02 - 16/11/02**	$MC\frac{\partial T_f}{\partial t} = -2.8728\langle\overline{T_f} - Ta\rangle$ **U_LA_C**=2.8728 (W/°C) **U_L** =3.38 (W/m^2°C)	$MC\frac{\partial T_f}{\partial t} = -2.89\langle\overline{T_f} - Ta\rangle$ **U_LA_C**= 2.89 (W/°C) **U_L** =3.4 (W/m^2°C)
ICSSWH **Without reflector and without insulator**	**30/12/02 - 08/02/03**	$MC\frac{\partial T_f}{\partial t} = -5.15\langle\overline{T_f} - Ta\rangle$ **U_LA_C**=5.15 (W/°C) **U_L** =6.06 (W/m^2°C)	$MC\frac{\partial T_f}{\partial t} = -5.168\langle\overline{T_f} - Ta\rangle$ **U_LA_C**= 5.168(W/°C) **U_L** =6.08 (W/m^2°C)

4. Conclusion

An ANN was used for the prediction of the temperatures of 4 tanks of ICSSWH, the neuronal characterization presents good agreement with experimental characterization, the use of the reflector and insulator has remarkable effect on the optical and thermal performances of this new prototype. The advantages of the ANN compared to classical methods are speed, simplicity and capacity to learn from examples.

Nomenclature

ANN	Artificial neural network
BRBP	Bayesian regularization back propagation
FFBP	Feed forward back propagation
ICSSWH	Integrated collector-storage solar water heater
A	Total system surface area, m^2
C_{cs}	Heat capacity of empty collector–storage unit, J kg^{-1} °C^{-1}
C_w	Heat capacity of water, J kg^{-1} °C^{-1}
F_E	System enthalpy retrieval factor, –
I	Solar irradiance on collector aperture, W/m^2
K	Collector incidence angle modifier, –
M_{cs}	Mass of empty collector–storage unit, kg
M_w	Mass of water in storage, kg
t	Time, s
T	Temperature of water in storage, °C
T_a	Ambient temperature, °C
T_f	Temperature of water in storage at sunset, °C
T_i	Temperature of water in storage at sunrise, °C

U_L Heat loss coefficient, W m^{-2} °C^{-1}

Greek symbols

η_o Collector optical efficiency, –

η Maximum useful efficiency (MUE), –

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