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ICS solar water heater study using artificial neural networks

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Abstract

In this paper we present a study in which a suitable Artificial Neural Network (ANN) and TRNSYS are combined in order to predict the performance of an Integrated Collector Storage (ICS) prototype. We use the experimental data that have been collected from outdoor tests of an ICS solar water heater with cylindrical water storage tank inside a CPC reflector trough, to train the ANN. The ANN is then used though the Excel interface (Type 62) in TRNSYS to model the annual performance of the system by running the model with the values of a typical meteorological year for Athens, Greece. In this way the specific capabilities of both approaches are combined, i.e., use of the radiation processing and modelling power of TRNSYS together with the "black box" modelling approach of ANNs. We present the details of the calculation steps of both methods that aim to the accurate prediction of the system performance and we show that this new method can be used effectively for such predictions.

Keywords: ICS solar water heaters, Artificial neural networks, TRNSYS

1. INTRODUCTION

Integrated Collector Storage (ICS) systems are solar water heaters that cover domestic needs for hot water in the range of 100–200 l per day and are considered as alternative solar devices to the well known thermosiphonic systems with flat plate or evacuated tube collectors. The storage tank of an ICS system has a dual function, i.e., to collect solar radiation and preserve the heat of the stored water. An effective thermal protection of the ICS storage tanks is difficult enough, as a significant part of their surface is exposed for the absorption of solar radiation. Double glazing, selective absorbing surface coatings and transparent insulating materials have been used for the thermal protection of the storage tank. Opaque thermal insulation however can only be placed on the non-illuminated parts of the tank surface and vacuum thermal protection is considered effective, mainly for ICS systems that consist of cylindrical tanks with small diameters. Cylindrical storage tanks are employed in most commercial ICS systems, as they resist the pressure of the water mains. The use of reflectors is considered necessary for ICS systems with cylindrical storage tank and depending on their orientation, reflector troughs of compound parabolic concentrator (CPC) or involute are used for the effective illumination of the storage tanks surfaces.

Extensive study on ICS solar systems has been performed at the University of Patras in Greece, where models of different designs have been tested and analysed [1–7]. On the other hand, at the Higher Technical Institute in Cyprus several solar energy systems (including ICS systems) have been studied using TRNSYS methodology and artificial neural networks (ANNs) [8–15]. Artificial neural networks differ from the traditional modelling approaches in that they are trained to learn solutions rather than being programmed to model a specific problem in the normal way. Neural networks are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non-linear problems, and once trained can perform predictions at very high speed. ANNs have been used in many engineering applications such as in control systems, in classification and in modelling complex process transformations.

The objective of this paper is to present a model which combines the capabilities of both methods. This is necessary because there is no readymade model of the particular ICS unit in TRNSYS and the suggested methodology is an alternative to the creation of a new TRNSYS component. This method can also be used in cases where systems or parts of them cannot be described analytically.

2. DESCRIPTION OF THE ICS UNIT

The design of the studied ICS unit is mainly based on the effective use of the non–uniform distribution of solar radiation on absorber surface, which is the result of using CPC reflector geometry. This principal design along with the partially thermal insulation (non-illuminated part) of the storage tank aim at achieving effective water heating combined with sufficient temperature stratification during daily operation and improving water temperature preservation during night. In the specific ICS model the solar radiation acceptance angle a has been chosen to be 90° to allow a significant part of diffused solar radiation to be collected. By this choice the total volume of the device can be significantly decreased. Finally, the suggested ICS system have lower cost and height compared to that of the usual flat plate collector system that has the same ratio of storage water volume per aperture area and hence, ICS system can be better harmonized to the surrounding architecture.

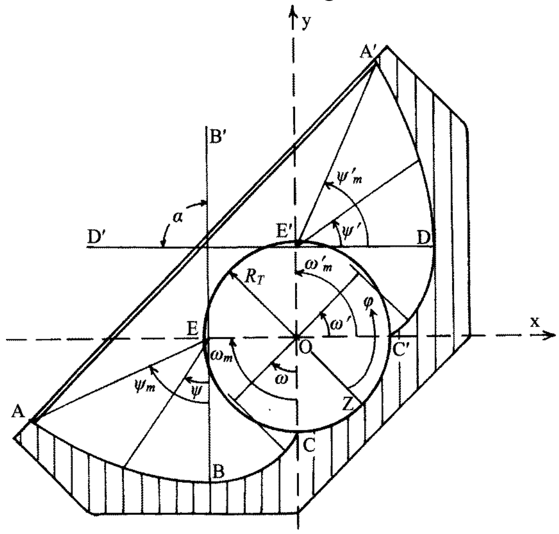

Fig. 1 Cross section of the ICS unit

In Fig. 1 we present the cross section of the experimental model ICS, which consists of truncated symmetric CPC reflectors with parabolic parts (AB), (DA′) and involute parts (BC), (C′D). The intersection point between the corresponding parabolas' axis BB′ and DD′ lies on the aperture surface (glazing) and determines the truncation level for the constructed experimental model. We consider R_T the radius of the cylindrical storage tank, ω and ω' the angles that are used to form the two involute reflector parts (BC) and (C′D) correspondingly, with ψ, ψ' the angles of the two parabolic reflector parts (AB) and (DA′) respectively. The maximum angles ω and ω' are taken $\omega_m = \omega'_m = 90°$, the maximum angles ψ and ψ' (rim angles) are $\psi = \psi' = 63.91°$ and the focal lengths are $f_1 = [BE] = \pi R_T/2$ and $f_2 = [DE'] = \pi\ R_T/\ 2$, respectively. The analytical mathematical equations of the reflector geometry and also the used materials of the construction of the ICS unit can be found in [6].

By experimentally testing the unit for more than a year a number of patterns were collected, every 30 minutes. These are separated into two files a training file comprising 5232 data sets and a validation files comprising 960 data sets. These files will be used for the training and validation of the artificial neural network. Both data sets comprise data during the day (heating) and during the night (cooling). It should be noted that all testing of the ICS unit was performed without draw off.

3. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) mimic somewhat the learning process of a human brain. Instead of complex rules and mathematical routines, ANNs are able to learn the key information patterns within a multidimensional information domain. In addition, the inherently noisy data does not seem to present a problem. According to Haykin [16], a neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects: (a) the knowledge is acquired by the network through a learning process, and (b) inter-neuron connection strengths, known as synaptic weights, are used to store the knowledge.

ANN models represent a new method in energy prediction. ANNs operate 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 a non-linear regression might perform. Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. They seem to simply ignore excess input data that are of minimal significance and concentrate instead on the more important inputs.

A training set is a group of matched input and output patterns used for training the network, usually by suitable adaptation of the synaptic weights. The outputs are the dependent variables that the network produces for the corresponding input. It is important that all the information needed by the network in order to learn, is supplied to it as a dataset. When each pattern is read, the network uses the input data to produce an output, which is then compared to the training pattern, i.e., the correct or desired output. If there is a difference, the connection weights are usually altered in such a direction that reduces the error. After the network has run through all the input patterns, and if the error is still greater than the maximum desired tolerance, the ANN runs again through all the input patterns repeatedly, until all the errors are within the required tolerance. When the training reaches a satisfactory level, the network holds the weights constant. The trained network can then be used to make decisions, identify patterns or define associations in new input data sets not used to train it.

3.1 Group Method Data Handling (GMDH) Neural Network (NN)

There are various methods that can be used to model the data. These could be based on simple regression analysis, multiple regression analysis, neural networks and many others. In this work, the neural network method is selected because of its accuracy. One type of neural networks, which is very suitable for the present application, is the group method of data handling (GMDH) neural network, which was used to model the data. GMDH works by building successive layers with links that are simple polynomial terms. These polynomial terms are created by using linear and non-linear regression. The initial layer is simply the input layer. The first layer created is made by computing regressions of the input variables and then choosing the best ones. The second layer is created by computing regressions of the values in the first layer along with the input variables. Again, only the best are chosen by the algorithm called survivors. This process continues until the network stops getting better (according to a prespecified selection criterion).

The resulting network can be represented as a complex polynomial description of the model. The complexity of the resulting polynomial depends on the variability of the training data. In some respects GMDH, it is very much like using regression analysis, but it is far more powerful than the latter. GMDH can build very complex models while avoiding overfitting problems. A by-product of GMDH is that it recognizes the best variables as it trains.

The GMDH network is implemented with polynomial terms in the links and a genetic component to decide how many layers are built. The result of training at the output layer can be represented as a polynomial function of the inputs. The layer building GMDH procedure continues as long as the evaluation criteria continue to diminish. GMDH algorithm then checks if this is so and continues or stops training. There may also be other conditions, which determine when training is stopped. The input data used in the network are the month (1-12), incidence angle, ambient temperature, total radiation on the collector aperture and wind velocity. The predicted parameter is the useful energy stored in the storage tank. From this energy the mean storage tank temperature can be determined during simulations. Additionally the incidence angle, used as input, inherently includes the day number and the time of the day, as it depends on these two parameters together with the particular inclination of the collector which is fixed.

The experimental data that have been collected from outdoor tests of an ICS solar water heater as described above have been used to train the GMDH ANN. The training dataset was learned by the ANN with good accuracy (R^2-value equal to 0.9392; the closer this value is to unity the better the training accuracy). Subsequently the validation data set was used, which is completely unknown to the network. This is used to test the ability of the network to produce accurate results. The R^2 value obtained in this case is 0.9383 and representative patterns are shown in Fig. 2 (left diagram).

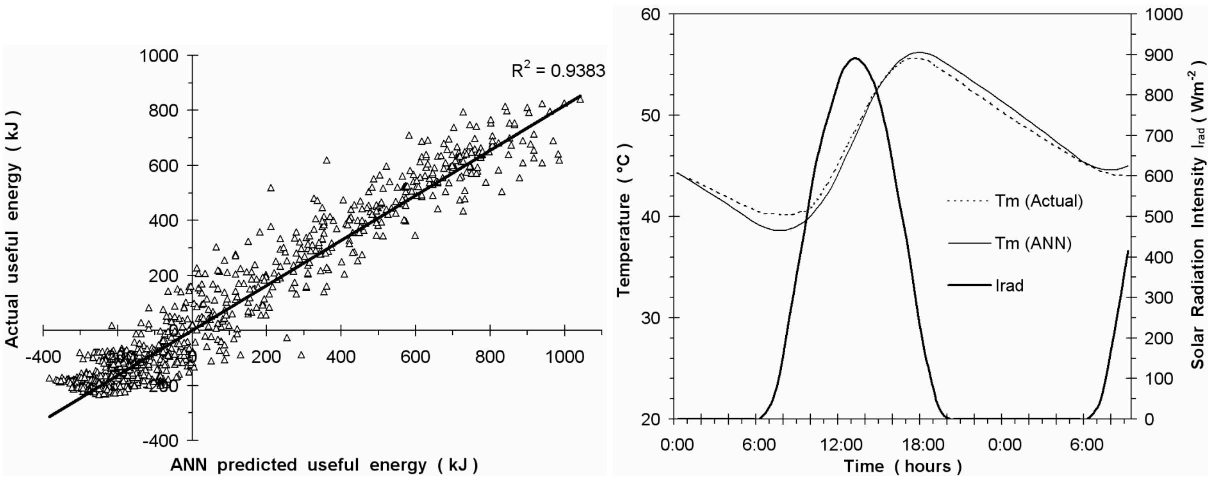

Fig. 2 Comparison between the actual and ANN predicted useful energy and water tank temperature.

A sample of actual and ANN predicted storage tank temperature for the 224th day of the year (August 12) is shown in Fig. 2 (right diagram). As can be seen the actual and ANN data are very close and the two lines are almost indistinguishable. It should be noted that the initial temperature at the beginning of the day is set equal to the actual storage tank temperature so as the two series have the same starting point. The final equation obtained from GMDH is quite complex:

$$
\begin{aligned}
Y= {} & 0.36*X_3+0.08*X_2-0.032*X_1+0.1*X_5-0.55-0.084*X_4+0.13*X_1^2+0.11*X_3^2+ \\
& 0.054*X_1^3+0.094*X_3^3+0.014*X_1*X_2-0.018*X_2*X_3-0.013*X_1*X_2*X_3+0.023*X_5^2+0.056*X_4^3- \\
& 0.12*X_5^3-0.02*X_1*X_4-0.0061*X_2*X_4-0.04*X_3*X_4-0.0098*X_1^2*X_4-0.0071*X_3^2*X_4- \\
& 0.0033*X_1^3*X_4-0.0079*X3^3*X_4-0.0012*X_1*X_2*X_4+0.00077*X_2*X_3*X_4+ \\
& 0.0011*X_1*X_2*X_3*X_4+0.0011*X_1*X_5-0.0085*X_2*X_5-0.034*X_3*X_5-0.0086*X_1^2*X_5- \\
& 0.0062*X_3^2*X_5-0.0029*X_1^3*X_5-0.0069*X_3^3*X_5-0.001*X_1*X_2*X_5+0.00067*X_2*X_3*X_5+ \\
& 0.00097*X_1*X_2*X_3*X_5+0.0037*X_4^2-0.0092*X_4*X_5-0.012*X_3*X_4*X_5-0.026*X_2^3
\end{aligned} \tag{1}
$$

All the data required by the GMDH need to be scaled from –1 to 1. Therefore, parameters X_1 to X_5 as well as useful energy, obtained from Y (Eq. 1) needs to be scaled in the same interval. This is done with:

$$y_i = \frac{2(x_i - x_{min})}{x_{max} - x_{min}} - 1 \tag{2}$$

In Eq. (1) the parameter X_1 stands for the month, X_2 for ambient temperature, X_3 for the total radiation on the collector aperture, X_4 for wind velocity and X_5 for the incidence angle. The latter (incidence angle) can easily be estimated from the solar radiation processor of TRNSYS.

4. SIMULATIONS

The ANN is then used though the Excel interface (Type 62) in TRNSYS [17] to model the annual performance of the system by running the model with the values of a typical meteorological year (TMY) of Athens, Greece. In this way the specific capabilities of both approaches are combined, i.e., use of the radiation process and modelling power of TRNSYS together with the "black box" modelling approach of ANNs. The time step used in TRNSYS was 30 minutes so as to be similar to the data used in the training of the ANN.

The results of the simulations for April 14 and August 12 and 13 are shown in Figs. 3 and 4 respectively. Both these figures are for no draw-off. Of course here the accuracy depends on how close the actual weather data during testing are to the weather data included in the TMY file. However, the small deviation recorded in mean storage tank temperature in the above figures is considered acceptable. As can be seen in both cases the maximum mean storage tank temperature reaches 50°C in April and 60°C in August whereas the lowest temperature which is the effect of tank cool down due to night time losses is 32°C in April and 40°C in August.

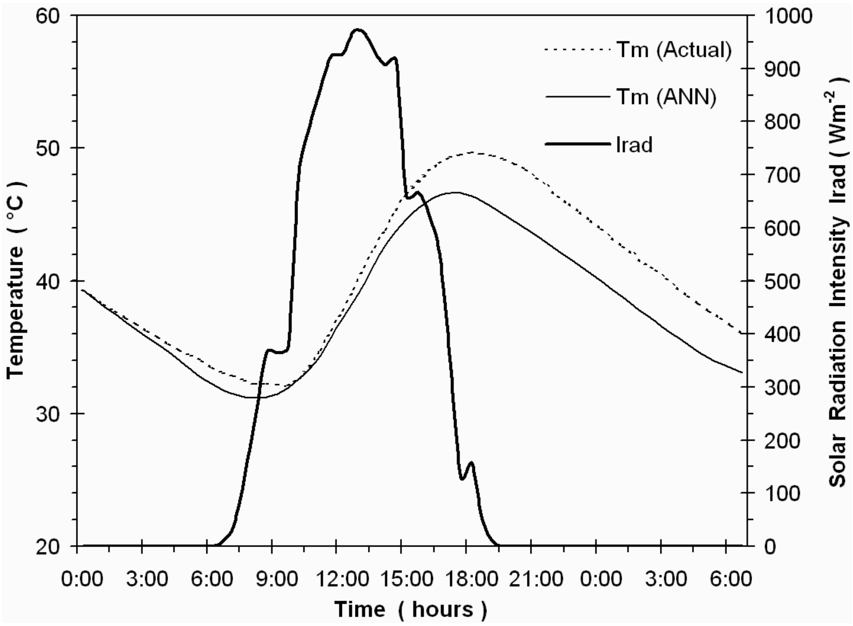

Fig. 3 Actual and ANN predicted storage tank temperature for April 14

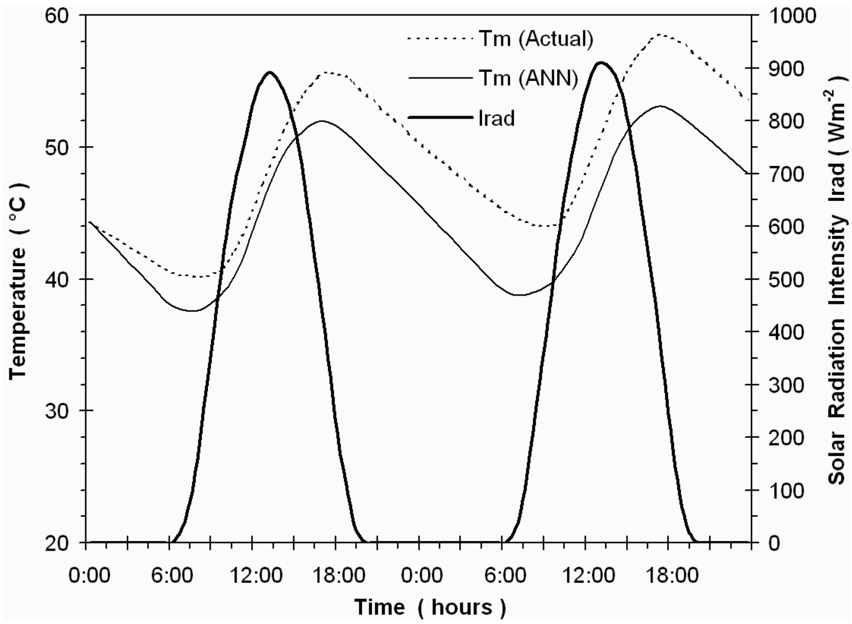

Fig. 4 Actual and ANN predicted storage tank temperature for August 12 and 13

Another test performed is to use certain patterns of draw off without the possibility of validation. Two such patterns were tested; a draw off pattern of 20 lt/hr from 19:00 till 22:00 (60 litters in total) and a pattern with 15 lt/hr draw off at 13:00, 15:00, 17:00 and 19:00. The results for August 12 are shown in Fig. 5. As can be seen the second pattern has more severe effect on the storage temperature because the temperature of the stored water has lower values at the time that the draw off pattern starts, although the solar radiation intensity has the maximum value at 12:30. In this point we should note that generally the time which the mean water tank temperature is maximized depends on a significant parameter used in the design of ICS systems. This parameter is the ratio of the stored water volume per aperture area, V_T / A_α (lt/m^2), which describes the sufficiency of the solar device for heating specific water volume and affect the time delay of the maximization of the mean water temperature to the corresponding maximization of the solar radiation intensity. In the specific device V_T / A_α equals to 100.28 lt/m^2.

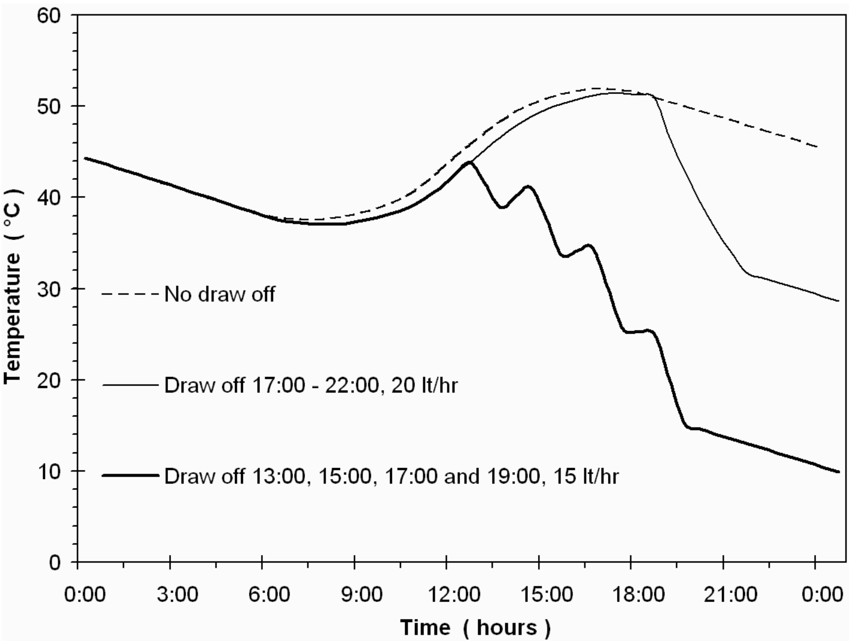

Fig. 5 Effect of draw off pattern on mean storage tank temperature

5. CONCLUSIONS

In this paper we present the details of the simulation of an integrated collector storage system with ANNs and TRNSYS. This is the only way to simulate such a system as no ready made routine is available in TRNSYS to model this type of systems. It is proved by the results that this new method can be used effectively for such predictions. The suggested methodology of combining ANNs and TRNSYS can be used to model other systems which are difficult to model analytically or their model is not available. We are planning to extent this method into the full year simulation of the system in order to be able to estimate the long-term performance prediction of such systems.

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