IDENTIFICATION OF THE TIME PARAMETERS OF SOLAR COLLECTORS
USING ARTIFICIAL NEURAL NETWORKS

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Abstract – The aim of the present study is to test artificial neural networks to enlarge the tool range for identification of the time parameters of solar collectors. In the first part of the study, it is reminded that two parameters fully describe the static behavior of flat plate collectors, and that two other parameters are necessary to fully describe the dynamic behavior of a flat plate solar collector. It is then shown that a heuristic method leads to the identification of collectors as third order systems. Then it is shown that RBF neural networks are able to accurately identify pure third order systems. This is validated by the computation of the correlation matrices. Then it is shown that these neural networks are able to identify the collectors as third order systems, and that there is no risk of over-learning. This is validated by the computation of the Euclidean distance between the collectors and their models, depending on the number of learning steps. When, in the tested cases, the distance between models varies from 0.3 to 0.65, the distance between a model and a collector is less than 0.03. Finally, it is shown that the neural networks are able to discriminate collectors that have close parameters: a difference of two percents for one parameter is identified by the proposed network.

1. INTRODUCTION

Flat solar collectors are widely used in many parts of the world. They encounter various radiation conditions. In some part of the world, radiation is stable; in other parts, clouds may come and radiation may vary quickly. For those conditions, the global efficiency of a solar system depends on the time response of the collector. It is then important to know the transient characteristics of collectors to make a comparison between collectors possible. To carry out such a comparison, a standard method can be used: the response of the collector to a step of solar radiation. Then it is necessary to determine the numerical values of the characteristics of the tested collectors. The aim of the present study is to propose a new method to determine these values.

In the first part of the study, the transient state governing equation is reminded. Knowing that two parameters fully describe the stationary state of the collector, it is shown that two other parameters fully describe the transient behavior of a collector. These parameters are called the time parameters.

In the second part of the study, artificial neural networks are tested. They are first tested on the identification of collectors as second order systems. It is shown that the discrimination ability depends on the size of the learning database. To avoid this phenomenon, neural networks are tested on the identification of collectors as third order systems.

2. GOVERNING EQUATIONS

Many types of flat solar collectors have been developed. Most of them may be modeled as one pass collectors. For such collectors the characteristics are given per square meter of the collector area. For a mathematical representation, the following characteristics are necessary: the thermal loss conductance \( K \), the optical efficiency \( \eta_0 \), the thermal capacity of the absorber \( T_{ca} \) and the global convection coefficient \( \alpha \). Other characteristics of the collector are needed, but they can easily be estimated: the length of the collector \( L \), the volume of fluid per square meter \( V \), the fluid characteristics \( \rho, c \) and the mass flow rate per square meter \( \dot{m} \). Under a radiation \( I \), and for an ambient temperature \( T_{\infty} \), the governing equation for the fluid temperature \( T_f \) is Eq. 1.

\[
\eta_0 I = K(T_f - T_{\infty}) + \frac{\alpha + K}{\alpha} L \dot{m} c \frac{\partial T_f}{\partial x} + \left( T_{ca} + \frac{\alpha}{\rho c V} \right) \frac{\partial^2 T_f}{\partial t^2} + \frac{T_{ca} \dot{m} c L}{\alpha} \frac{\partial^2 T_f}{\partial x \partial t} + \frac{\rho c V T_{ca}}{\alpha} \frac{\partial^2 T_f}{\partial t^2} \]

(1)

Under steady state conditions, Eq. 1 becomes Eq. 2.

\[
\eta_0 I = K(T_f - T_{\infty}) + \frac{\alpha + K}{\alpha} L \dot{m} c \frac{\partial T_f}{\partial x} \]

(2)

It may be written as Eq. 3.

\[
\frac{\eta_0}{K} I = (T_f - T_{\infty}) + \frac{\alpha + K}{\alpha} L \dot{m} c \frac{\partial T_f}{\partial x} \]

(3)
Eq. 3 shows that two parameters fully describe the steady state of a collector: \( \frac{\eta_0}{K} \) and \( \frac{\alpha + K}{\alpha K} \). These parameters can be identified using a standard testing method.

To know how many parameters describe the transient state, Eq. 1 must be written as Eq. 4.

\[
\eta_0 I = (r_f - r_a) + \frac{\alpha + K}{\alpha K} L m c \frac{\partial T_f}{\partial t} + \left( \frac{T_{ca}}{K} + \frac{\alpha + K}{\alpha K} \rho c V \right) \frac{\partial T_f}{\partial t} + \frac{T_{ca}}{K} \frac{1}{\alpha} m c L \frac{\partial^2 T_f}{\partial x^2} + \frac{T_{ca}}{K} \frac{1}{\alpha} \rho c V \frac{\partial^2 T_f}{\partial t^2}
\]

Apart from the two previously determined parameters, it can be seen that two time parameters are sufficient to describe the dynamic behavior of a collector: \( \frac{T_{ca}}{K} \) and \( \frac{1}{\alpha} \). It is possible to conclude that a two parameters model should be sufficient to accurately identify a collector.

3. IDENTIFICATION OF THE TIME PARAMETERS

It has been shown that artificial neural networks are able to identify the time parameters of electrical heaters (Lalot and Lecoeuche, 2000), it has also been shown that artificial neural networks could play an important role in identification of solar systems (Kalogirou, 1999) (Kalogirou, 2000) and in solar radiation forecasting (Heinemann et al., 1999). Hence, it is legitimate to test artificial neural networks to enlarge the tool range for identification of the time parameters of solar collectors. To show the feasibility of such an identification, it is supposed here that the first two parameters are known.

The values have been fixed to: \( \frac{\eta_0}{K} = 0.1 \), \( \frac{\alpha + K}{\alpha K} = 0.138 \).

The ambient temperature and the inlet fluid temperature have been fixed to 20°C, the normal solar radiation has been fixed to 800 W/m². Four theoretical collectors will be studied, and Eq. 4 will be numerically solved. Fig. 1 gives the values (in S.I. units) of the collectors.

<table>
<thead>
<tr>
<th>Collector</th>
<th>( \eta_0 )</th>
<th>( K )</th>
<th>( \alpha )</th>
<th>( T_{ca} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>0.8266</td>
<td>8.266</td>
<td>60</td>
<td>7000</td>
</tr>
<tr>
<td>C2</td>
<td>0.8266</td>
<td>8.266</td>
<td>60</td>
<td>14000</td>
</tr>
<tr>
<td>C3</td>
<td>0.7834</td>
<td>7.834</td>
<td>100</td>
<td>14000</td>
</tr>
<tr>
<td>C4</td>
<td>0.7834</td>
<td>7.834</td>
<td>100</td>
<td>13720</td>
</tr>
</tbody>
</table>

Fig. 1: characteristics of the studied collectors

It can be seen that there is a large difference of thermal capacity for the first two collectors, and that this difference is small (2%) for the last two collectors. As the collectors have the same static parameters, the steady state temperature will be the same. So, it is possible to define a dimensionless temperature:

\[
\theta = \frac{T_f(L,t) - T_{inlet}}{T_f(L,\infty) - T_{inlet}}
\]

In the studied conditions, inlet fluid temperature equals to the ambient temperature, \( \theta \) varies from 0 to unity.

3.1 Second order systems

As a two parameters model is looked for, second order systems have been tested. Fig. 2 shows the time response curves of the collectors and of second order systems that have been heuristically found.

![Fig. 2: Time response of collectors and of second order systems](image)

It can be seen that, apart from the short times, a good agreement may be found.

3.1.1 Definition of the identification domain

A second order system is characterized by the following transfer function:

\[
F(s) = \frac{1}{1 + 2 \zeta \frac{s}{\omega_n} + s^2/\omega_n^2}
\]

As the global shape of the time response curve of the collectors is known, it is possible to reduce the study of the second order systems to those that present a damping factor higher than unity. In that case, the response of a second order system to a step function may be written as follows:

\[
F(t) = 1 + \frac{s_2}{s_1 - s_2} \exp(s_1 t) - \frac{s_1}{s_1 - s_2} \exp(s_2 t)
\]
with:

\[ s_1 = -\omega_n \left( \zeta + \sqrt{\zeta^2 - 1} \right) \quad \text{and} \quad s_2 = -\omega_n \left( \zeta - \sqrt{\zeta^2 - 1} \right). \]

So, it is possible to characterize a second order system by either \( \zeta \) and \( \omega_n \), or by \( s_1 \) and \( s_2 \). It has been chosen here to identify the damping factor \( \zeta \) and the pulsation \( \omega_n \) in the following ranges:

\[ 1.01 \leq \zeta \leq 1.53 \quad \text{and} \quad 0.01 \leq \omega_n \leq 0.019. \]

These ranges define a identification domain, and it is obvious that the studied collectors fall within this domain.

3.1.2 Artificial neural networks capabilities

The first artificial neuron has been introduced in 1943 by Mc Culloch and Pitts. Since then, many neural networks have been proposed (Marren et al., 1990): the Perceptrons, the Hamming networks, the Radial Basis Function Networks (RBFN), the Probabilist Neural Networks, the Self-Organizing Maps, the Learning Vector Quantization, … They differ one another by the type of neurons, their architecture, their learning rule. All these characteristics determine their main application field: classification, optimization, identification… For the latter application, feedforward networks (Figure 3) such as Multi-layered Perceptron and RBFN are mainly used.

Each RBF neuron of the hidden layer estimates the conditional probability density that the input vector belongs to a particular region of the input space. Its connection weights (\( W_k \)) with the input layer represent the center of this region. The size of this region is defined by \( \sigma_k \). The Radial Function is a Gaussian function, the summation function is the Euclidean distance between the input vector (\( I \)) and the weight vector (\( W_k \)). The calculation of the parameters \( s_k \) and the weights \( W_k \) is made during a supervised learning phase: the chosen learning rule is the Extended Delta-Bar-Delta.

In any case, once the architecture is chosen, the difficulties are to find the number of hidden layers, the number of neurons in each layer, the type of neural activity function, the size of the learning database and the learning rule. As there is no straightforward approach, only experiments lead to an efficient solution.

3.2 Identification of 2nd order systems using RBFN

The first approach consists in choosing a standard 3 layers RBFN architecture. In this case, the input layer has as many neurons as the size of the input vector; the only hidden layer has as many neurons as models contained in the learning database; the output layer consists of two neurons: one represents the pulsation, the other represents the damping factor. In our case, the input vector consists of samples of time response to a step function. For the learning phase, it is necessary to use a learning database. It consists of a set of couples of input and output vectors. From a known output vector, an input vector is generated using theoretical second order systems. In the first trial, the learning database consists of 130 input vectors representing 9 points of time response curves. After 5,000,000 learning steps, although the correlation matrixes are correct for pure second order systems (Fig. 5), the identification is not correct (Fig. 6).
It is possible to modify the neural network to get a better identification. For that, it is necessary to introduce a second hidden layer, and to change the output function of the first layer neurons to the "one-active" type. In this special case, in less than 40,000 learning steps, the neural network is able to perfectly learn the database; the error is exactly null. The identification is better (Fig. 7).

But, as the output of the first layer is of the "one-active" type, the network is not able to correctly interpolate solutions. So, the discrimination ability of the network depends on the size of the database.

As can be seen in Fig. 7, the beginning of the curves of the models are still not close to the curves of the collectors. This leads to the test of identification of collectors by third order systems.

3.2 Third order systems
As a two parameters model is looked for, and as third order systems should have three parameters, it will be tried to fix one of these parameters. Fig. 8 shows the time response curves of the collectors and of third order systems that have been heuristically found.

It can be seen that, even for the short times, a good agreement may be found.
3.2.1 Definition of the identification domain

A third order system is characterized by the following transfer function:

$$F(s) = \frac{l}{s(s+a)(s+b)(s+c)}$$

that corresponds to the following temporal function:

$$F(t) = 1 - \frac{a^2}{(a-b)(a-c)} e^{-t/a} +$$

$$\frac{b^2}{(a-b)(b-c)} e^{-t/b} + \frac{c^2}{(a-c)(c-b)} e^{-t/c}$$

To get a two parameters model, parameter $b$ has been assigned the value 10. Then it is necessary to identify $a$ and $c$. The following domain has been investigated:

$$25 \leq a \leq 55 \quad 50 \leq c \leq 250$$

First, it has been verified that neural networks are able to identify pure third order systems. Fig. 9 shows the correlation matrixes for the parameters $a$ and $c$. These matrixes are given for 5,000,000 learning steps when the learning error is exactly null. It can be seen that the identification is correct.

The risk of over-learning has been studied, on one hand by looking at the test error, and on the other hand by computing the distance between a collector and its model. The distance between a collector and its model is defined by:

$$d_{\text{collector, model}} = \sqrt{\sum_{t=1}^{500} \left[ \theta_{\text{collector}}(t_i) - \theta_{\text{model}}(t_i) \right]^2}$$

Concerning the test error, it has been found that between 500,000 and 5,000,000 learning steps, the test error stays stable at 0.1045. Concerning the distance between a collector and its model, it can be seen in Fig. 10, that after 1,000,000 learning steps there is no significant evolution.

The risk of over-learning being avoided, it is possible to give a comparison between the response curves (Fig. 11).

It can be seen that at short times the identification is better than with second order systems. To get an idea of the quality of the identification, it is possible to compare the distance between the collectors themselves and between the collectors and their models. It has been found that, when the distance between collectors varies from 0.3 to 0.65, the distance between a collector and its model is less than 0.05, and is mostly less than 0.02.
A detailed view of the response curves shows that the network is able to discriminate the two collectors that have close characteristics (Fig. 12).

Fig. 12: Comparison of collectors and identified third order models

4. CONCLUSIONS

It has been shown that an artificial neural network can be a powerful tool for identification. It has been shown that collectors may be considered as second order systems, but that in that case, the discrimination ability of the network is not very high. It has also been shown that collectors may be considered has third order systems.

Future studies will address the possibility not to fix one parameter in the third order model, and the characterization of actual collectors.

REFERENCES


