ARTIFICIAL NEURAL NETWORKS IN MODELLING THE HEAT-UP RESPONSE OF A SOLAR STEAM GENERATING PLANT

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ABSTRACT

An experimental solar steam generator, consisting of a parabolic trough collector, a high pressure steam circulation circuit, and a suitable flash vessel has been constructed and tested with respect to establishing its thermodynamic performance during heat-up. Preliminary tests demonstrated that the heat-up system response, and hence the heat-up energy requirement has a marked effect on performance. The most important parameters affecting this response are the dimensions, the inventory of the flash vessel, and the prevailing environmental conditions. Experimental data were obtained and used to train an artificial neural network in order to implement a mapping which may be useful to system designers. The trained network predicted well the response of the system, as indicated by an obtained statistical R-squared value of 0.999 and a maximum deviation between predicted and actual values confined to less than 3.9%. This degree of accuracy is acceptable in the design of such systems. This result is even more important, having in mind the fact that the system was tested during its heat-up, under transient conditions, which make it very difficult to model analytically.

INTRODUCTION

Parabolic trough collectors (PTC) are frequently employed in solar steam generation, because temperatures as high as 300°C can be obtained without any serious degradation in the collector efficiency. A typical application of this type of system is the Southern California power plants, known as Solar Electric Generating Systems (SEGS), which have a total installed capacity of 354 MWe (Kearney & Price 1992). The system described in this report, is capable of generating 22 kg of steam in one day, at 100°C and atmospheric pressure.

Three methods have been employed to generate steam using PTCs (Murphy & Keneth 1982):

* The direct or in-situ concept, in which two phase flow is allowed in the collector receiver so that steam is generated directly.
* The steam-flash concept, in which pressurised water is heated in the collector and then flashed to steam in a separate vessel.
* The unfired-boiler concept, in which a heat-transfer fluid (e.g. 3M Santotherm 55) is circulated through the collector and steam is generated via heat-exchange in an unfired boiler.

The flash steam generation concept has certain advantages with respect to other systems due to the superiority of water as a heat transfer fluid compared to heat transfer oils, the relatively low capital cost of the system since no heat exchanger is required, and the avoidance of any flow instability problems which usually appear in the in-situ systems.

The power of neural networks in modelling complex mappings, and in implementing system identifications has been demonstrated in various occasions (Kohonen 1984, Ito 1992, Nabhan & Zomaya 1994). Such work encouraged many researchers to explore the possibility of using neural network models in real world applications such as control systems, data classification, and modelling of complex process transformations (Eberlein 1988, Guez *et. al*. 1988, Neocleous & Schizas, 1994).

In this study, an artificial neural network has been used to model the transient heat-up response of the system, by employing measured data from an experimental steam generating plant located at the Higher Technical Institute in Cyprus. The input data are those that are easily measurable, i.e. environmental conditions and certain physical parameters (dimensions and sizes). The outputs are the measured temperatures, obtained over the heat-up period at different positions on the system.

DESCRIPTION OF THE STEAM GENERATING SYSTEM

The system consists of a parabolic trough collector of $3.5 m^2$ aperture area, a flash vessel, a high pressure circulating pump, and the associated pipework, as shown in Fig. 1.

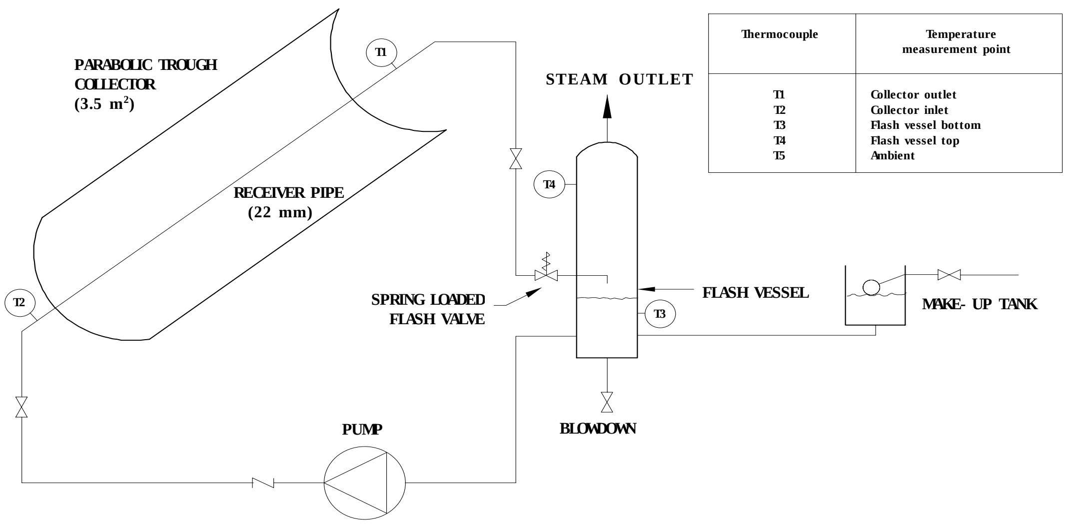

Fig. 1. The complete steam generation system

Water drawn from the flash vessel, is circulated through the receiver of the solar collector at high pressure in order to inhibit evaporation in the receiver, and hence prevent flow instability problems. The high temperature, high pressure water is flashed into steam at atmospheric pressure in the flash vessel which acts as a steam separator.

SYSTEM PRE-HEAT ENERGY EVALUATION

In order to maximise the system steam production, the heat-up energy requirements should be kept to a minimum. This is because energy invested in the preheating of the flash vessel is inevitably lost due to the nature of the diurnal cycle. The losses during the long overnight shutdown return the vessel to near ambient conditions each morning. This reduction could be readily achieved by reducing the water inventory and also by optimising the flash vessel dimensions and construction in order to lower the system thermal capacity and losses. In an earlier report (Kalogirou *et. al*. 1995), the problem of system optimisation through variation of the flash vessel design was studied in detail. Three different vessels have been used as shown in Table 1.

Table 1. Flash vessels physical dimensions

Flash vessel number	Outside diameter (mm)	Inside diameter (mm)	Wall thickness (mm)	Vessel height (mm)	Inventory (Kg)
#1	94	51	1.2	600	0.6
#2	105	65	2.0	600	0.7
#3	115	75	2.5	800	1.5

Typical set of data, obtained during the heat-up of the system from cold, is shown in Fig. 2. The system reaches the end of the pre-heat cycle when the temperature at the flash vessel top (T4) equals the temperature at flash vessel bottom (T3). This condition indicates that steam is now being produced at a steady rate and that the flash vessel has reached the steady state temperature. For the system equipped with flash vessel #2 this is achieved after approximately 35 minutes (see Fig.2). During this period the insolation was approximately 690 W/m^2 which represents a total energy available to the collector of 4.3 MJ. It can be seen from Fig. 2 that the temperature at the top of the flash vessel (T4), slowly increases by conduction from the bottom of the vessel until the collector outlet temperature reaches 100^{o}C. When this happens the temperature increases more rapidly but more energy is still needed, (about 0.25 MJ) to pre-heat this part of the vessel. The steam produced during this period is condensed on the relatively cold vessel walls until the temperature reaches the value of T3, at which point the pre-heat cycle is completed and the system starts generating useful steam.

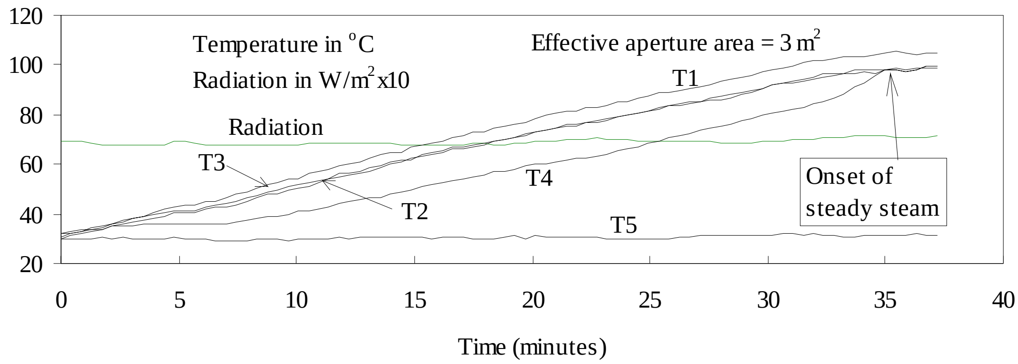

Fig. 2. System pre-heat cycle graph (Flash Vessel #2)

ARTIFICIAL NEURAL NETWORK MODEL OF TRANSIENT RESPONSE OF THE SYSTEM

Experimental data for the three system cases have been used to train an artificial neural network. The actual data is a set of values of time, ambient temperature (Ta), the effective aperture area (A), solar radiation (I), flash vessel content and the flash vessel dimensions of height, diameter and thickness. The network architecture selected is the Ward type (Neuroshell 2) with eight neurons in each hidden layer. The Ward type architectures allow multiple hidden slabs with different activation functions. The learning algorithm used was the standard backpropagation. Eight element inputs have been used corresponding to the values of the input parameters, listed above, as an eight-element input vector of the training data set. The output is a four element vector corresponding to the values of T1, T2, T3 and T4. The learning rate was set to 0.1 and the momentum factor to 0.5. The weights were initialised to a value of 0.3. From a total of 396 patterns, 47 were randomly selected to be used as test patters and the remaining 346 were used for training the network. The input data were learned, as shown in Fig. 3 with excellent accuracy with R^2 values as shown in Table 2. In fact the matching between predicted and measured values in all cases is so close that the two lines are almost indistinguishable.

Table 2. Statistical analysis of program predictions and resulting maximum percentage error

Temperature	Correlation coefficient	R^2-value	Maximum % error
T1	0.999	0.9987	3.9
T2	1.000	0.9996	1.3
T3	1.000	0.9992	2.3
T4	1.000	0.9992	3.3

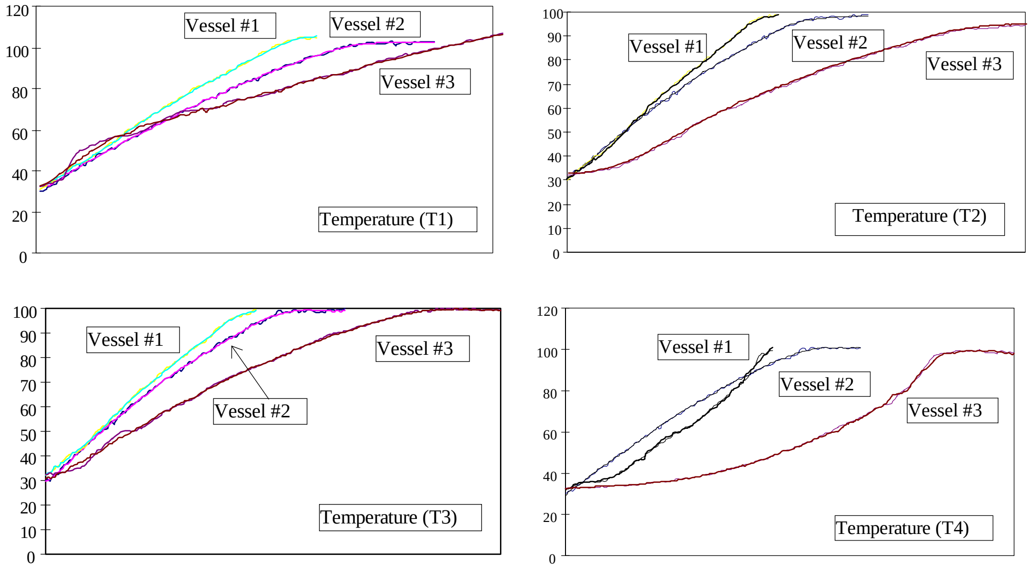

Fig. 3. Comparison of actual and predicted heat-up response for the temperatures indicated

CONCLUSIONS

The modelling of the system presented here was able to predict pre-heat completion times within 3.9%. This is considered very adequate and thus the neural network can be used effectively for this type of predictions. This will greatly facilitate the work of people working in this field as the analytical modelling of such systems under transient conditions is very difficult.

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