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004 - Fault diagnostic method for a water heating system based on continuous model assessment and adaptation

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Abstract

The objective of this work is the development of an automatic solar water heater (SWH) fault diagnostic system (FDS). The latter consists of a modelling module and a diagnosis module. A data acquisition system measures the temperatures at four locations of the SWH system (outlet of the water tank; inlet of the collector array; outlet of the collector array; inlet of the water tank). In the modelling module a number of artificial neural networks (ANN) are used, trained with the very first values when the system is fault free. Then, the neural networks are able to predict the fault-free temperatures and compare them to actual values. When the differences are low, the corresponding networks are unchanged. On the contrary the networks are retrained. Then the diagnosis module analyses the difference between the current connection weights and the initial weights. When a persistent significant modification occurs, a flag is set to signify that a default is present in the SWH.

The system can predict three types of faults: collector faults and faults in insulation of the pipes connecting the collector with the storage tank (to and from the tank) and these are indicated with suitable labels. It is shown that all faults can be detected well before the end of the drifts, without any false alarm, when the networks and thresholds are well tuned and that the observation window has the right size. It is shown that this does not depend on the draw off profile.

Keywords: fault diagnostic, model adaptation, neural network, water heating system

1. Introduction

Solar water heating (SWH) systems are not usually equipped with any fault diagnostic system (FDS). Any faults are usually identified either by regular inspection by servicing personnel or when the system is not producing appropriate quantities of hot water, which is the most frequent. Usually people forget the existence of the solar system and this is inspected only after hot water is not available, indicating some problems. This results in problematic operation of the systems for long periods of time, which reduce the effectiveness and viability of the systems. Primarily works present the possibility of on-site determination of faults [1-2]. But the drifts were of a step-by-step type. As it has been shown that continuous drifts can be analysed by neural networks in heat exchangers [3-5], ANN has been chosen here to test such tools. In particular, a method based on neural models is presented according to the study detailed in [6] which shows that a continuous assessment of a model and its adaptation is efficient. In a first part, the solar system is presented along with the drifts that are taken into account. The drift detection tool is detailed in the second part, and results are given in the third part.

2. Description of the water heating system

The solar system considered in this work is a large hot water production system suitable for a small hotel, blocks of flats, offices or similar applications. Although the FDS system developed can be applied to small systems as well it is thought that the expenditure required would not balance the extra benefits incurred in such cases and in domestic applications the users are usually more sensitive to the maintenance of their own system in comparison with the maintenance staff of a hotel for example or the tenants of a multi building installation where everybody but really nobody is responsible. The system schematic is shown in Fig. 1. The system consists of 40 m^2 of collectors, a differential thermostat (not shown in Fig. 1) and a 2000 L storage tank. The system is also equipped with a data acquisition system which measures the temperatures at four locations of the SWH system; the collector array outlet (T1), the storage tank inlet (T2), the storage tank outlet (T3) and the collector array inlet (T4). The global solar radiation, the ambient temperature, and the pump state (on/off) are also recorded.

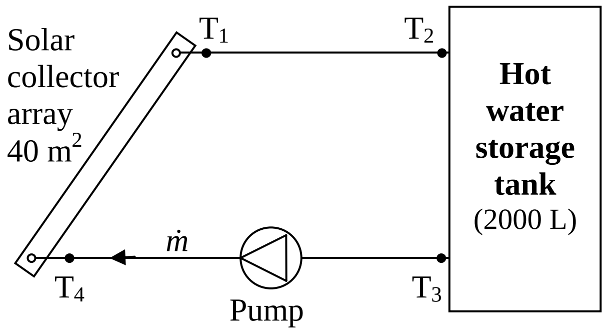

Fig. 1 Schematic diagram of the solar system

In fact, a TRNSYS model is used to simulate the system. Two draw off profiles have been used. The first one is repeated day after day, the second one is computed using the free generator developed at the Univeristät Marburg [7] and used in [8]. Being totally different, these profiles will show that the results do no depend on them. In a real application, the temperature readings would be affected by noise. So, it has been decided to add random noise to each computed temperature. It has to be noted that the time step is one hour.

Four drifts or defaults are taken into account in this study. For the collector, two parameters are considered: F' (linked to the fin efficiency), and U_L (linked to the thermal insulation); for details see TRNSYS manual. For F', a progressive decrease is computed so that the value decreases from 0.7 to 0.6. For U_L, a sudden increase is considered (from 3 to 4 $W/m^2.K$) followed by a progressive increase (from 4 to 5 $W/m^2.K$). For the connecting pipes, the variations of the U value are similar to the variations of the U_L value. These drifts will be shown in the last section when presenting the results. It has to be noted that it has been necessary to write our own components for TRNSYS to be able to read the values from files, which allow continuous variations of the parameters (one value corresponding to one hour).

The drifts have been both considered separately and combined. In the latter case, which leads to the lowest performance of the system, the yearly increase of the auxiliary electrical power needed to deliver the hot water is less than 7.5%. It can be concluded that if the FDS is able to detect the faults before the end of the drifts, it is sufficiently efficient.

3. Description of the fault diagnostic method

Figure 2 shows the overall procedure used in this work, and each block is described hereafter. But before the description of the method, it is necessary to show that neural networks are able to accurately model the components of the solar system. In fact three parts of the system are monitored: the collector array, the connecting pipe from the tank to the collectors, and the return connecting pipe. As two components are similar, only two networks will be presented here.

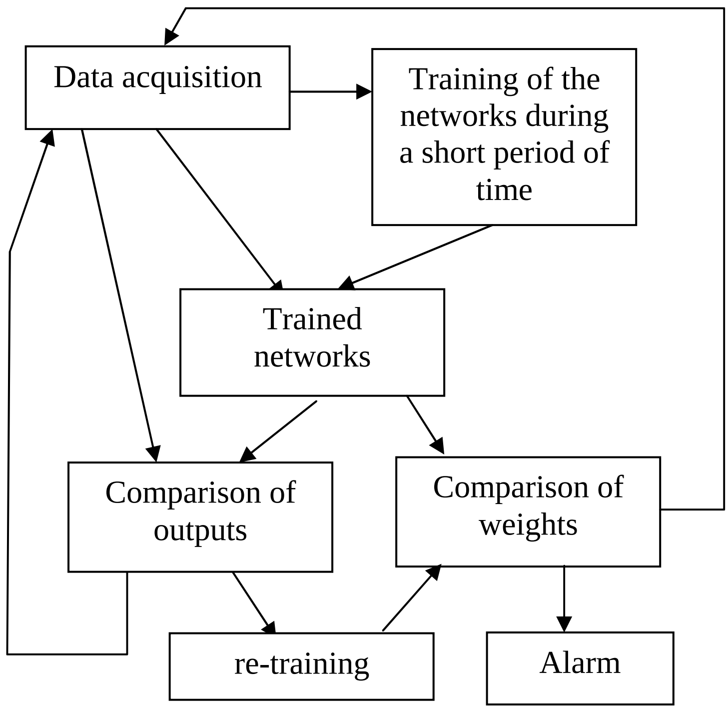

Fig. 2 Schematic diagram of the FDS

3.1. The neural networks

To model the collector array as simply as possible, a very small network is used. Using a unique non linear neuron on the hidden layer and a linear output neuron leads to good results when considering modeling the array when the fluid is flowing during two consecutive hours; which means that the system is in a quasi steady state and that it is not necessary to use complex models as presented in [9]. This is also similar to the conclusion given in [10] stating that parameter estimation of a solar collector array is reliable when high temperatures are obtained within the collectors. The inputs are the inlet temperature T4, the global radiation, the ambient temperature. The output is the outlet temperature T1. Figure 3 shows the differential (in %) between estimated values and actual values when the system is stable all year long. Due to the fact that the system is more likely to run two consecutive hours in summer, the error is lower during these months. Nevertheless, the maximum error is less than 1%. The equation representing the estimated values versus the actual values is written as: $T_{est} = 1.0003\ T_{act} - 0.0244$, the regression R value is then 0.9996.

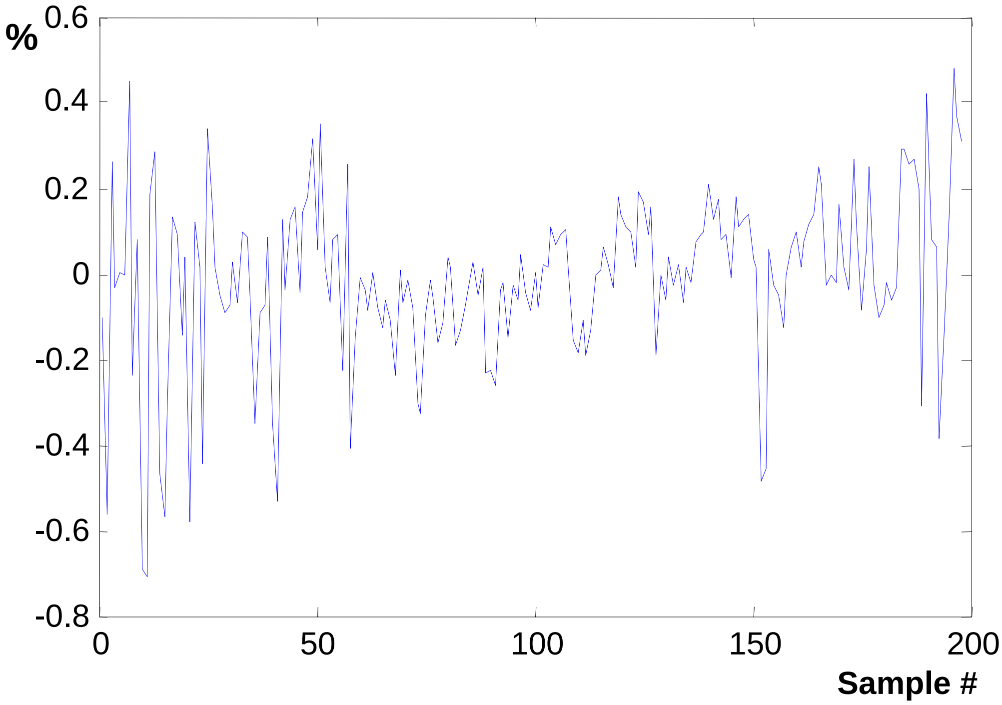

Fig.3 Differential between estimated and actual values for the collector array

For the connecting pipes a similar network is used, the inputs are the inlet temperature of the pipe, the ambient temperature, and the global radiation. The output is the outlet temperature of the pipe. In this case the regression R value are closer to unity, the difference is -2.6 10^{-6}, and the equation is

$$T_{est} = 0.9997\ T_{act} - 0.0174$$

3.2 The FDS procedure

The kernel of the system is the neural networks. So, it is necessary to consider a first step to train the networks. This period should be as short as possible because during this period the system has to be inspected regularly to be sure that nothing has happened (e.g. it is necessary to clean the collectors). It has been found that getting 30 values with a sampling period of 1 hour is a good compromise between sensitivity of the procedure and initial length.

At the end of the initialization period, three networks are available. They are used to estimate the temperatures. The latter are compared to the acquired temperatures through the computation of the RMSE. If the error is very small, the initial connection weights are stored in a matrix. If the error is higher than a threshold (0.05 for the collector array, 0.015 for the connecting pipes), the networks are re-trained. The new connection weights are stored in the connection weights matrix. If a given number of consecutive connection weights are different from the initial weights, an alarm is fired. It has been found that 5 consecutive values are sufficient, and do not lead to long delays between the fault and its detection.

4. Results

To generate the data, the typical meteorological year (TMY) files of Nicosia have been considered. Figure 4 shows the detection time for the F' drift considering the two draw off profiles.

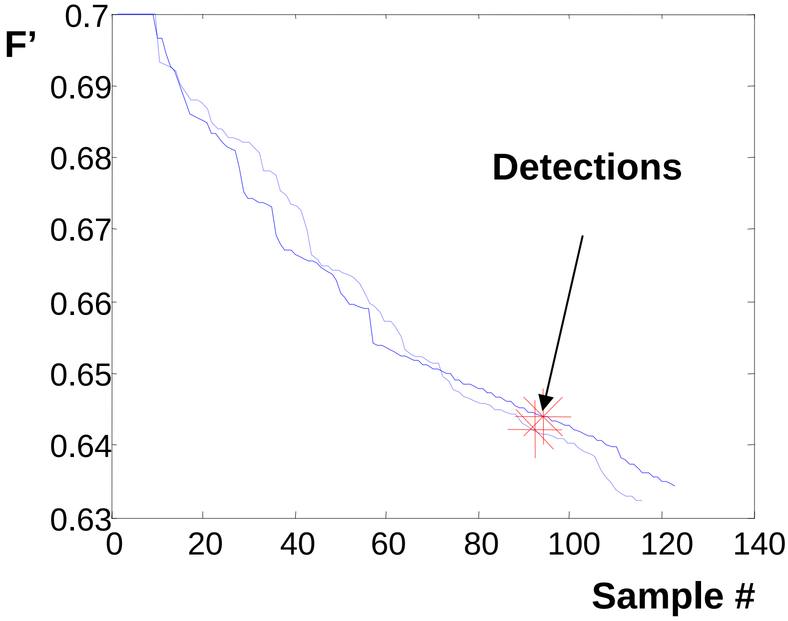

Fig. 4 Detection of the F' drift for two different draw off profiles

Although it seems that the detection is quite late, a plot of the temperatures about the detection time shows that it would be very difficult to detect the drift by the simple analysis of the temperatures (Fig. 5).

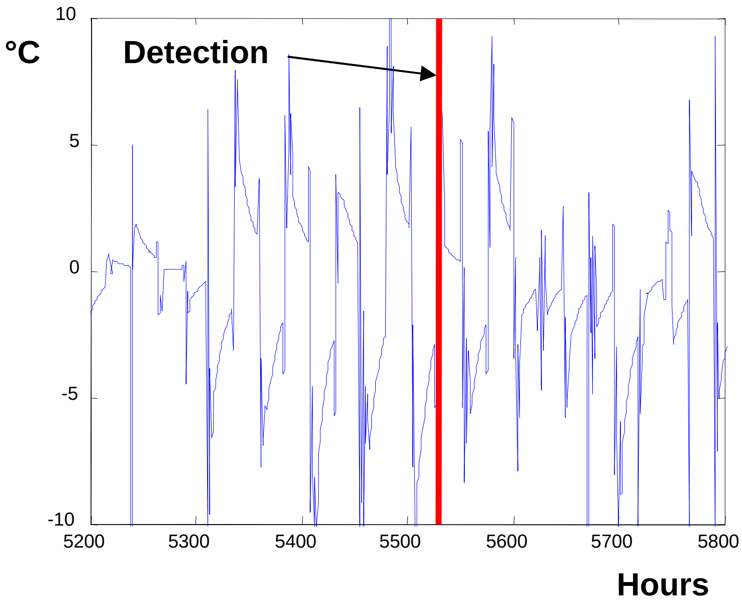

Fig. 5 Differential between temperatures when the system is stable all year long and when F' evolves

Figure 6 shows the detection time for the U_L drift. On the one hand, it can be noted that a combined drift leads to an earlier detection. On the other hand, it has been checked that the defaults on the connecting pipes do not lead to any detection by the analysis of the collector array data.

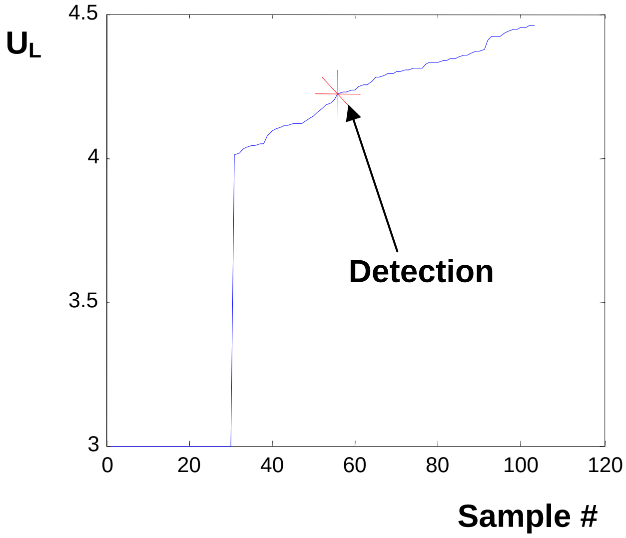

Figure 6: Detection of the U_L drift

Figure 7 shows the detection time for the U value of the connecting pipe between the outlet of the storage tank and the inlet of the collector, which includes the pump.

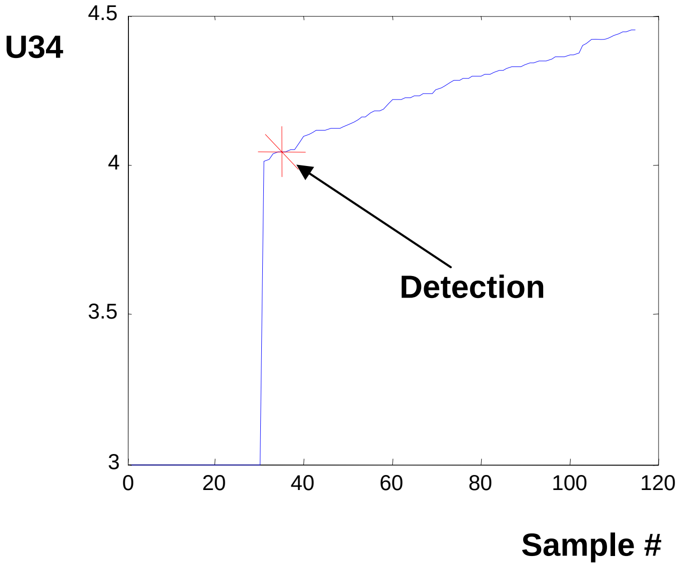

Fig. 7 Detection of the U34 drift

5. Conclusions

An on-line fault diagnostic system has been presented. The main advantage of this system is that it does not need a long training period. It has been shown that the drifts are detected well before the increase of the auxiliary electrical power is higher than 7.5%. This means that the FDS is sensitive. As the neural networks are very simple, this should not be a problem to implement the FDS in real world applications.

Acknowledgements

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