MODELING AND CONTROL OF A WATER GAS HEATER WITH NEURO FUZZY TECHNIQUES

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Abstract: This paper presents the work in progress concerning the use of Neuro-Fuzzy techniques for modeling and control of a real system. The main objective is to control the output water temperature of one water gas heater, with changes in the water flow and/or changes in the setpoint. The steps taken to arrive at the direct and inverse models, using ANFIS, are described and the results of controlling the water gas heater with a Direct Inverse Control, Internal Model Control and Additive Feedforward Control strategies are presented.

Keywords: Hybrid Methods, Neuro-Fuzzy Modeling and Control (ANFIS), Direct Inverse Control, Internal Model Control and Additive Feedforward Control.

1. Introduction

The present paper describes the modeling and control of a prototype of a water gas heater. The main goal is to model and control the output water temperature of the water gas heater, which depends, essentially, of three input variables: input water temperature (cold water), water flow and gas flow applied to the burner. In section 2 the gas heater and the complete system are described allowing the reader to have a comprehension of the problems that will be detailed in later sections. Section 3 reports the architecture used to identify the model of the system. Section 4 focuses on the three control structures used, pointing out their characteristics. Section 5 reports the results achieved with the three control strategies. At last, section 6 present the conclusions and give some details of the future work.

2. The Water Gas Heater System

The overall system can be divided in 3 main blocks: the water gas heater, one personal computer and one interface board (see figure 1).

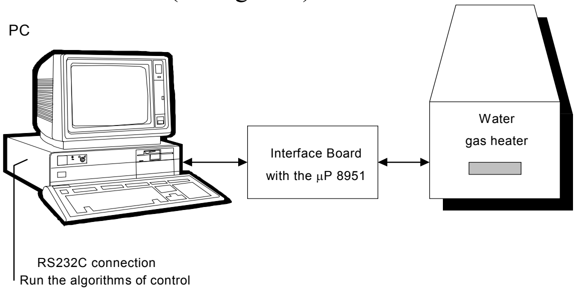


Fig. 1. The system main blocks.

The water gas heater is a multiple input single output (MISO) system. The input variables are, the cold water temperature (cwt), the water flow (wf) and the applied gas flow into the burner (gf is proportional to the percentage of a pulse wide modulation (PWM) signal applied to the gas valve that regulates the applied gas flow into the burner). The output variable is the hot water temperature (hwt).
The hot water temperature is a variable that is function of the cold water temperature, the water flow and the gas flow, Eq.1.

$$hwt = f(cwt, wf, gf) \qquad \text{(Eq.1)}$$

Under normal circumstances, the operating range of the hot water temperature is limited between 30ºC and 60ºC. The range of variation of cold water temperature, in Portugal, is between 5ºC and 25ºC. This range of variation depends on the climatic conditions of the region and the season of the year.
The operating range of the water flow is between 3 and 15 litters / minute. This range depends on the physic characteristics of the water gas heater (the burner and the permutation chamber) which means that depends of the maximum power (MaxP) of the water gas heater given by the Eq.2.

$$\begin{aligned} MaxP &= (hwt - cwt) \times wf \\ &= \Delta t \times wf \quad \text{Kcal/min} \qquad \text{(Eq.2)} \end{aligned}$$

There are water gas heaters with several maximum powers, like 125, 225, 325 and 400 Kcal/min, that will allow ranges of water flow from 3 to 5 l/min to 12 to 15 l/min.

Figure 2 shows the working zones and the lower and higher limits of working of a water gas heater with the maximum power of 325 Kcal/min.

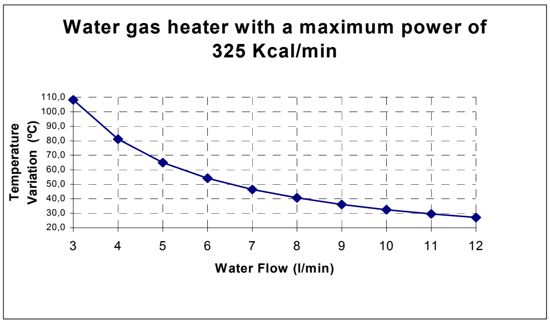


Fig. 2. Working limits of a 325 Kcal/min water gas heater.

2.1. The Water Gas Heater

The water gas heater is physically composed by a gas burner, a permutation chamber, a ventilator, two gas valves and several sensors used for control and security as is shown on figure 3.

The gas burner can burn natural or propane gas. This burner heats the copper permutation chamber where the cold water enters from bellow and circulates. The amount of power applied to the water is controlled by one "proportional-type" gas valve driven by a pulse-width modulated (PWM) signal. The cold and hot water temperature sensors are inexpensive negative coefficient resistors (NTC). The water flow sensor is an optical linear sensor. The overheat, ionisation and ventilation sensors are all binary-type sensors.

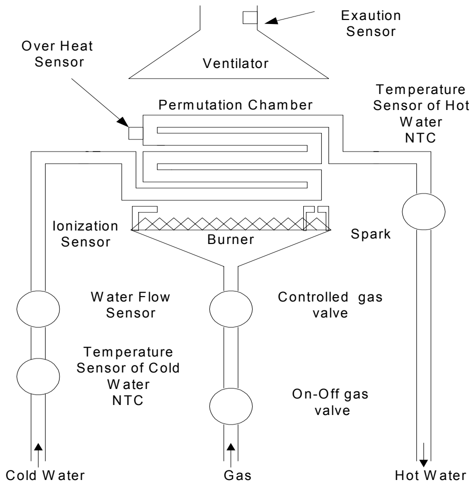


Fig. 3. Schematic of a water gas heater with its sensors and actuators.

The controlled gas valve shows an almost linear behaviour between the percentage of the PWM input signal and the water temperature increase. This can be seen in figure 4.

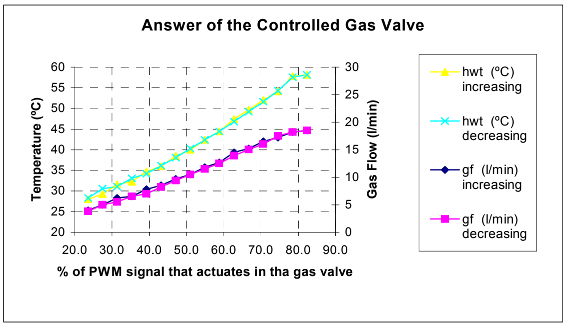


Fig. 4. Characterisation of the controlled gas valve with a fixed water flow of 10 l/min.

To a fixed gas flow and cold water temperature, the permutation chamber presents a non linear function between the water flow and the hot water temperature as can be seen in figure 5. This non linearity was already expected because of the characteristics of power of the water gas heater presented in figure 2.

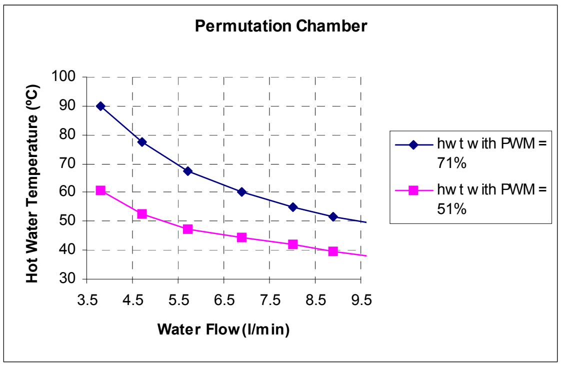


Fig. 5. Characterisation of the permutation chamber for a fixed cold water temperature of 22ºC.

In order to get a useful model we need to know the following parameters:

- Sampling time
- Dead time
- Order of the system (space lag)

To calculate the "best" sampling time a step signal was applied in the gas valve and the rise time of the hot water temperature signal was measured. Using Eq. 3 gives the sampling time h [9] as chosen equal to 1 second.

$$h = \text{sampling time} <= \frac{\text{rise time}}{5\ \text{to}10} \qquad \text{(Eq.3)}$$

The step response also shown that the water gas heater has a dead time of 4 seconds between the variation of the input signal and the hot water temperature variation. This dead time is due to the time that is necessary for the gas to arrive at the burner, to be burned and to heat the permutation chamber.

In order to know if there is a dead time between the water flow and hot water temperature, it was applied a step signal of water flow was applied and the results show that there is no dead time except the one generated by the sampling.
Finally, the water gas heater can be represented in a detailed form, by the blocks illustrated in Figure 6.

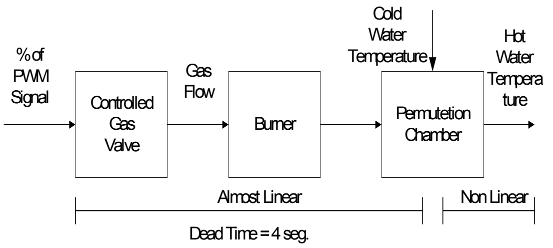


Fig. 6. Diagram of blocks of the water gas heater.

About the order of the system, the water gas heater behaves like a first order system. From the step response it is clear that there is a dominant time constant.

2.2. The Interface Board
The interface board has three modules, all controlled by the flash-type microcontroller PHILIPS 89C51RD. The three modules are:

- Sensors and actuators module
- Security module
- Communications module

The sensors and actuators module is responsible to read the cold and hot water temperatures, the overheat sensor status (temperature of the metallic structure), water flow, exhaustion sensor status (ventilator works with a on/off control) and the ionisation state (flame detection).
At the level of the actuator devices there is the spark, which is responsible for the ignition period, the on/off gas valve used for security and the controlled gas valve that defines the gas flow that feeds the burner.
The security module is responsible for the supervision and control of the security conditions. This module monitors and controls the overheat sensor, the ventilator, the ionisation, the water flow and the ignition period. It also controls the start up of the water gas heater.
The communication module is responsible for the connection between the interface board and the computer. This connection is made by a serial communication using RS232C.

2.3. The Personal Computer
The personal computer has the function of reception and sending data from and to the interface board and performs all the control and training algorithms. All the software runs under the MATLAB environment. In the future the PC will be eliminated and the microcontroller will execute the control algorithms.

Figure 7 shows one photo of the system with the water gas heater, the board of interface and the PC.

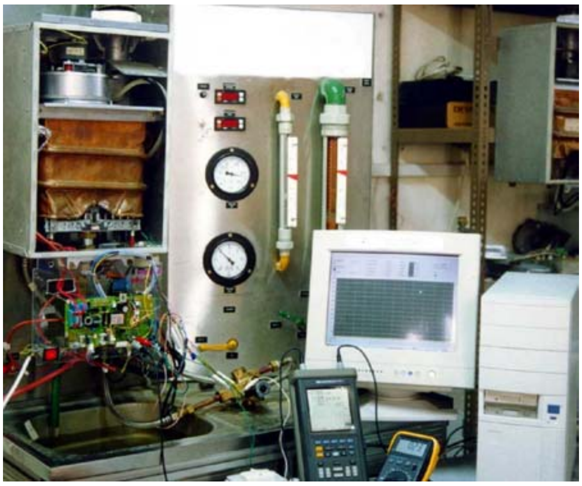


Fig. 7. Photo of the real system.

3. Identification
Because the system shows non-linearities the use of hybrid networks like ANFIS (Adaptive Neuro Fuzzy Inference Architecture) for the direct and inverse model was considered to be a possible approach.
This hybrid method takes advantage of the capacity that the fuzzy logic has to store knowledge and of the capacity of learning of the neural networks.
According to Jang [1] with this architecture it is possible to approach any linear or non-linear function (universal approximator).

3.1. Identification data and ANFIS structures
The identification data has been chosen to respect two important requirements: frequency and amplitude spectrum wide enough [8]. With this aim, and with a sampling period of 1 second, the operation of collecting data was made successfully.
Using the data collected and divided into training and test sets, direct and inverse models were identified using Adaptive Neuro Fuzzy Inference Systems, (ANFIS) an hybrid learning technique explained in [1].
The training structures used for the direct and inverse models can be depicted in figures 8 and 9. These structures are the most common solutions for training models and are described in several articles like in [4] and [8].
The ANFIS structure used to obtain the model and the inverse model contains 8 rules. It has three inputs with two membership functions each (bell shaped with three non-linear parameters) and one output. The total number of fitting parameters is 50, including 18 premise parameters (6*3 non-linear) and 32 consequent parameters (8*4 linear).
Considering that k=n*h, where k is the time instant, n is the iteration and h the sampling time, the direct

model inputs are the hot water temperature at time k-1, hwt(k-1), the gas control signal at time k-4, gf(k-4), and the water flow signal at time k-1, wf(k-1). The output is the prediction of the hot water temperature at time k, hwt(k).

$$\hat{hwt}(k) = f(hwt(k-1), wf(k-1), gf(k-4))\ (Eq.4)$$

For the inverse model, the inputs are the hot water temperature at time k+4, hwt(k+4), the hot water temperature at time k+3, hwt(k+3) and the water flow signal at time k+3, wf(k+3). The output is the prediction of the control gas signal at time k, gf(k).

In practice it is impossible to preview the future of the water flow, because the water flow is an independent variable and not controlled. So instead of using water flow signal at time k+3 was used, the water flow signal at time k-1, wf(k-1).

$$\hat{gf}(k) = f(hwt(k+4), hwt(k+3), wf(k-1))\ (Eq.5)$$

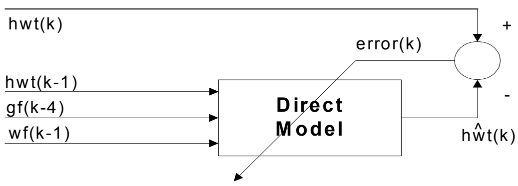


Fig. 8. Structure for direct model training.

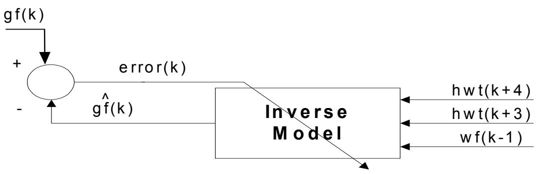


Fig. 9. Structure for inverse model training.

The cold water temperature could be placed as an extra input of the model. So the model will be:

$$\hat{hwt}(k) = f(hwt(k-1), wf(k-1), gf(k-4), cwt(k-1))$$
(Eq.6)

However, because this variable change very slowed (order of days or months) it becomes difficult to get useful training data. So it was assumed that the cold water temperature is a load applied to the system.

In the present case, the training data has been acquired with cold water temperature constant and equal to 18ºC.

The following pictures show the training signals and the outputs of the direct and inverse model. The identification procedures were performed using the **MATLAB** Fuzzy Logic Toolbox [5] tools. The training was performed off-line.

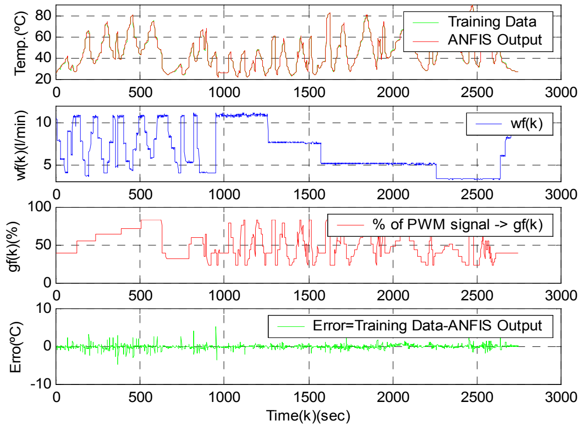


Fig. 10. Model answer to training set.

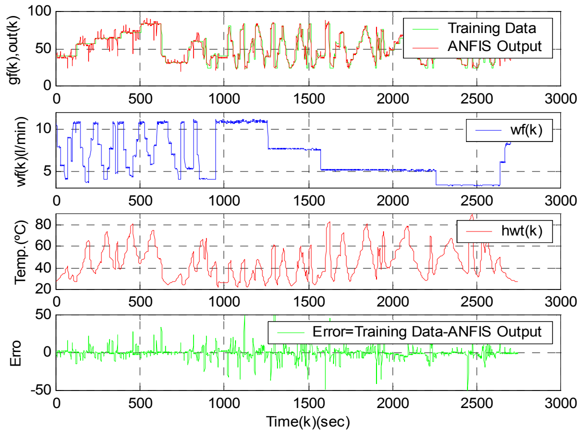


Fig. 11. Inverse model answer to training set.

From the graphics of figures 10 and 11 it is easy to see that the modeling errors are small enough. It is also clear that the error of the inverse model is greater than the direct one. This can be justified by the fact that one of the inputs of the inverse model is a past value of the water flow instead of the future value.

4. Control Structures

Many control structures concerning the use of direct and inverse models have been presented in the literature but in the aim of this article only three will be presented: Direct Inverse Control (DIC), Internal Model Control (IMC) and Additive Feedforward Control (AFFC).

4.1. Direct Inverse Control (DIC).

Direct inverse control is the simplest solution. The inverse model is connected in series with the plant (figure 12). If the inverse model is of good quality, the output will follow the reference with four second of delay (dead time of the gas heater).

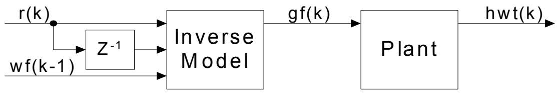


Fig. 12. Structure for DIC.

4.2. Internal Model Control (IMC).

Internal Model Control is a solution that consists of connecting in series, the inverse model of the plant and in parallel with the plant, the direct model. The difference between the output of the model and the output of the plant will generate an error that will be feedback [6]. This solution can be seen in figure 13.
This controller usually presents a very active control signal. To avoid this it was used a first-order low pass filter with a time constant of approximately 3 seconds.

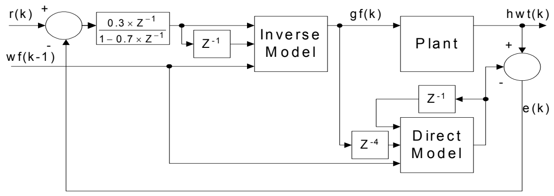
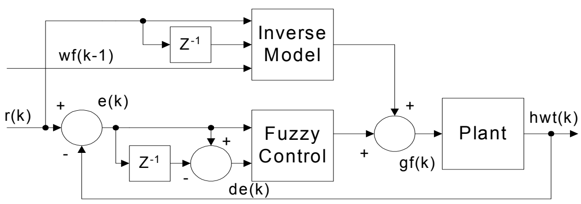


Fig. 13. Structure for IMC.

4.3. Additive Feedforward Control (AFFC).

Additive Feedforward Control is a solution that adds to an existing (but not satisfactory functioning) feedback controller an additional inverse process controller as shown in figure 14.
The base feedback controller used was a Fuzzy Logic Controller tuned manually. The addition of the inverse process controller will improve the performance of the AFFC controller.

Fig. 14. Structure for AFFC.



5. The Real Time Control Action

When the simulation results were considered satisfactory, the controllers were tested directly in the water gas heater.
The three control structures were tested with setpoint and water flow variations and with the temperature of the cold water constant and equal to 23ºC.

The application of the DIC controller shows the results presented in Figure 15.

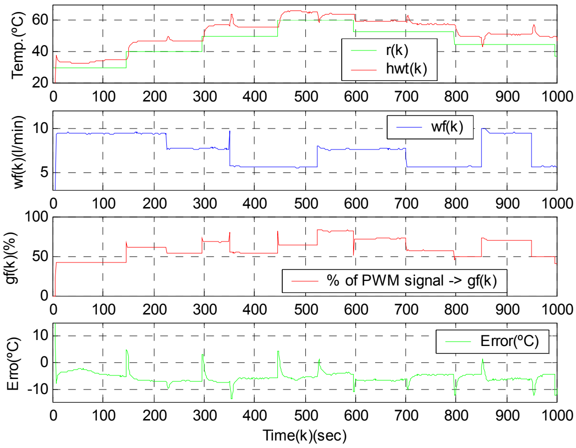


Fig. 15. Hot water temperature control using DIC.

Being almost an open loop solution the DIC solution shows an error in stationary state due to the fact that the cold water temperature is different from the one used to obtain the training data. In this case the inverse model does not match the inverse behaviour of the real system.

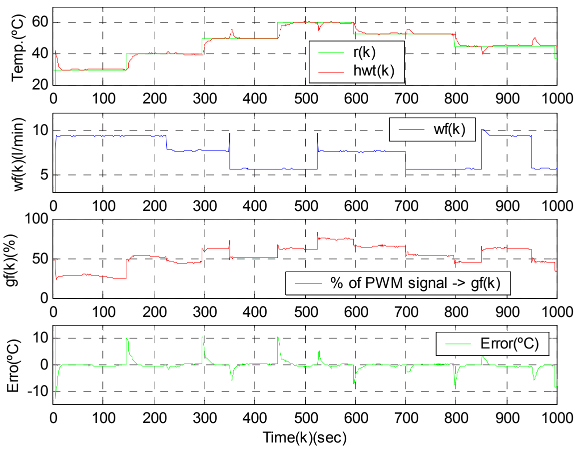


Fig. 16. Hot water temperature control using IMC.

As can be seen in Figure 16, the results do not present error in stationary state. The closed loop action eliminates the error in spite of the different cold water temperature.

The results for the AFFC solution can be seen in Figure 17.

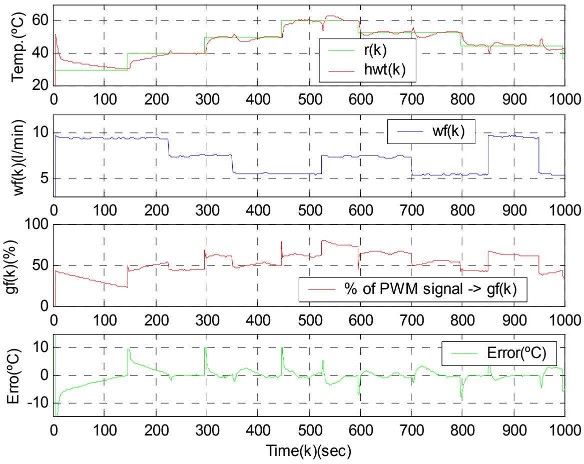


Fig. 17. Hot water temperature control using AFFC.

As can be seen in Figure 17 the controller shows no stationary error.

To compare the results, we calculate the mean square error for three control solutions.

MSE	DIC	IMC	AFFC
Complete Set	36.96	6.23	9.38

Table 1. Mean Square Error – Comparison between the three solutions.

From the observed results, we can conclude that, for this system, under these conditions the best strategy of control is the IMC solution.

6. Conclusions and Future Work

About the tested controllers, the following can be affirmed:

- the direct inverse controller presents good results when load in the system does not exist;
- the internal model controller is the one, under this conditions, that presents the better results of the three tested controllers. It presents a closed loop that compensates the existent load;
- the additive feedforwad controller, also presents good results, however, due to the fact the inverse model is not accurate under the testing conditions it deviates the controller from the zero steady state error and the fuzzy controller (not optimised) has to correct this error.

The results above show that the direct and inverse models must include the cold water temperature data as an extra input. This will probably lead to better results for all the controllers.
The problem of having a system with two inputs with different dead times is also a problem to be solved.

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