Scheduling of PID Controllers by Means of a Neural Network with Application to a Solar Power Plant.
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Scheduling of PID controllers by means of a Neural Network With Application to a Solar Power Plant

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Abstract - This paper concerns the application of a neural network control strategy to the distributed collector field of a solar power plant. The neural network is trained based on measured data from the plant providing a way of scheduling between a set of PID controllers, a priori tuned in different operating points by means of Takahashi rules. The present work consists in a hybrid scheme combining the potentialities of neural networks for approximation purposes with the well-know theory and widespread industrial application of PID techniques.

Experimental results collected at Plataforma Solar de Almeria (Spain), show the effectiveness of the proposed approach.

Keywords: Neural networks; Input space partitioning; Scheduling PID control; Solar power plants.

I. INTRODUCTION

The main control requirement in a solar power plant is to maintain the outlet oil temperature of the collector field at a constant pre-specified value. One of the main features of the plant is that its primary energy source, the solar radiation, cannot be manipulated by the control system. Moreover, since the solar radiation changes substantially during plant operation, due to the daily solar cycle, the atmospheric conditions such as cloud cover, humidity and air transparency. Thus, significant variations in the dynamics of the field (e.g. the response rate and time delay), corresponding to different operating conditions may occur. Therefore, it is difficult to obtain a satisfactory control performance over the whole operating range with a fixed linear controller.

In order to overcome these difficulties adaptive control schemes using local linear models of the plant, within self-tuning [1], [2], or predictive controllers frameworks [3], have been proposed. Other approaches have suggested intelligent control techniques, such as neural networks [4], [5], or fuzzy systems [6], [7], [8]. Another alternative is to use distinct controllers for the different operating points and to provide a switching strategy to select the most appropriate controller for each operating point. In this context, Rato *et al* [9] have suggested a switching scheme based on the MUSMAR algorithm and Henriques *et al* [10] have presented a control strategy based on a PID control design with a fuzzy logic-scheduling supervisor. This idea was followed in this work.

Control scheduling techniques are well-known strategies appropriate to deal with systems whose dynamics change with the operating conditions. They involve three main tasks: partition the operation region into several local models, designing a local controller for each region and switching between local controllers [11].

The partitioning of the operating regime space into a number of sets leads to a reduction of the problem complexity by discarding irrelevant interactions and thus considering regions that are easier to handle. It involves the selection of variables that allows characterising different operating conditions and the appropriate mapping, which relates them with a given operating point. Obtaining these variables and the respective mapping is the main drawback of control scheduling approaches.

Concerning the representation of each local region, there has been much enthusiasm in the past few years about local modelling approaches, see [12] and [13] for a review. Such methods include the well-known Takagi-Sugeno Fuzzy models [14] and local model networks [15]. Once obtained a local representation there are several techniques to design a local controller. Following a conventional approach the design of a controller usually requires a good analytical model of the process under consideration. However, solar power plants are very complex and, as a result, it is very difficult to derive a useful analytical model.

One the other hand, traditional PID controllers have some advantages, such as the dynamic performance reached in well-defined nominal operating conditions and their industrial widespread. They are simple to implement, they need very little knowledge about the process and they can successfully regulate many industrial processes with different specifications [16].

The incorporation of PID controllers within scheduling mechanisms can be support by the following [17]: *i*) PID scheduling schemes are able to cope with most of the cases that leave the PID under-optimal [18]; *ii*) the combination of a PID control law and a scheduling strategy can lead to a highly nonlinear control law, which can allow increasing significantly the robustness of the control system [19]; *iii*) the effectiveness of this scheme is validated by practice, since most of control methods in process industry are actually a combination of simple PID controllers with control actions performed by human operators in order to adjust the PID parameters according to the operating point.

The Accurex field is a particular process where the main variables that define the different operating points, are known and accessible. Additionally, a lot of experimental data characterising the plant input-output behaviour is available. Therefore, the partitioning of the input space is reduced, in this particular case, to establishing a suitable mapping, which can be set as an approximation problem. One the other hand, it is known that the most interesting feature of neural networks is their ability to learn and generalise nonlinear functions, from input-output data examples. Consequently they provide an obvious methodology to be used concerning the learning of the scheduler relationship [20]. In this way, they avoid the need to manually design a scheduling mapping or determine a suitable inference system.

In this context, Maia and Resende [21] have presented a neural controller technique for MIMO plants. Their technique is based on the linearisation of a nonlinear plant model at different operating points. A global nonlinear controller is obtained by scheduling the gains of the local operating designs. In [22] an on-line approach to scheduling control of a nonlinear plant was discused. The technique consists in a partition algorithm used to split the plant operation space into several regions and a mechanism that designs a linear controller for each region. A radial basis function neural network is considered for on-line interpolation of the controller parameters of the different regions. This type of technique has been applied successfully in several fields such as hydroelectric generation [23], communication systems [24], robotic manipulators [25] and aircraft flight control systems [26].

The present work intends to exploit a simple and effective structure that uses a neural network for scheduling a set of PID controllers, previously tuned for each operating point by means of Takahashi rules [27]. It provides a bridge between the field of neural networks and linear control methods. The main goal is to investigate the combination of the potentialities of neural networks for approximate nonlinear mappings and the well-know features of PID control techniques.

The paper is organized as follows: section 2 gives a short description of the solar power plant. In section 3 the neural network scheduling structure is described as well as the local PID controllers tuning. Section 4 deals with the application of the proposed methodology to the solar power plant and, finally, section 5 concludes the paper.

II. THE SOLAR POWER PLANT

The Accurex distributed solar collector field at Plataforma Solar de Almeria (PSA) is located at the desert of Tabernas, in south of Spain, and is quite well described in [28]. The field consists of 480 distributed solar collectors arranged in 20 rows, which form 10 parallel loops. Each loop is 172 m long and the total aperture surface is $2672 m^2$, enabling to provide $1.2 MW$ peak of thermal power. A schematic diagram of the plant is shown in Figure 1.

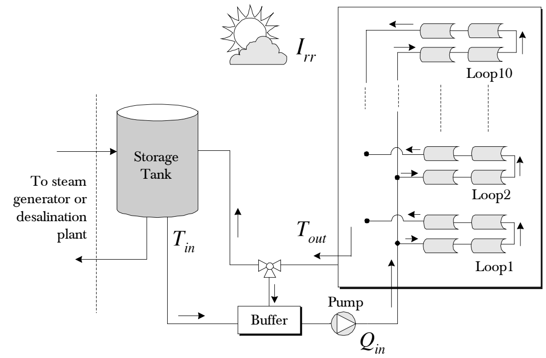


Figure 1. Schematic diagram of the Accurex field.

The cold inlet synthetic oil is collected from the bottom of the storage tank and is passed through the field by using a pump at the field inlet. After having picked up the heat transferred from the tube walls the heated fluid is fed to the storage tank to be used for electrical energy generation or feeding a heat exchanger of the desalination plant. The fluid used for heat transmission is the Santotherm 55, which is a synthetic hydrocarbon with a maximum film temperature of $318°C$ and autoignition temperature of $357°C$. Therefore $300°C$ is set as the maximum temperature allowed. If the system reaches this temperature in any loop the collectors are sent into desteer for safety reasons.

Each collector uses parabolic mirrors to concentrate the radiation in a receiver tube being the field also provided with a sun-tracking system that causes the mirrors to revolve around an axis parallel to that of the pipe. The manipulated variable in the plant is the oil flow rate, Q_{in}, being the main goal to regulate the outlet field oil temperature, T_{out}, at a desired value, T_{ref}. The main disturbances are the solar radiation, I_{rr}, and the inlet oil temperature, T_{in}. The pump has maximum flow rate of $12\ l/s$ and the lowest flow rate permitted is $1.6\ l/s$ but, by safety reasons, it is set between $2\ l/s$ and $9\ l/s$. If the pump stops the field goes automatically into desteer, in order to avoid overheating the oil in the parabolic-trough loops.

III. SCHEDULING BETWEEN LOCAL CONTROLLERS WITH NEURAL NETWORKS

A. Scheduling Variables to the Accurex Field

It is known that the plant dynamics is quite influenced by the oil flow rate, Q_{in}, provided by the pump. Thus, the strategy followed here considers this variable as the one used in the scheduling mechanism, enabling to infer the operating point. The variables that directly influence the operating conditions are the desired output temperature, T_{ref}, the solar radiation, I_{rr}, and the inlet oil temperature, T_{in}, being the auxiliary information vector given by:

$$x = \begin{bmatrix} T_{ref} \\ T_{in} \\ I_{rr} \end{bmatrix} \quad (1)$$

The scheduling variable is then computed as follows:

$$Q_{in} = f(T_{ref}, T_{in}, I_{rr}) = f(x) \quad (2)$$

However, the actual value of Q_{in} is unknown in advance. Instead of using directly the flow rate as the scheduling variable it was used the output from a neural network.

B. Neural Network Structure

Given the approximation capabilities of feedforward neural networks it is assumed that there exists a neural network, described by (3), and shown in Figure 2 able to describe the input-output scheduling mechanism.

$$Q_{nn} = W2\,(\,\sigma\,(W1\,x + B1)\,) \quad (3)$$

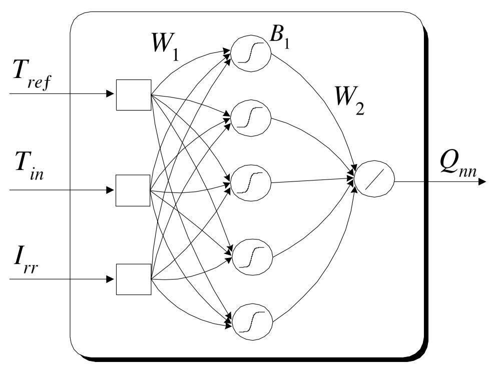


Figure 2. Feedforward neural network scheduler.

W_1 and W_2 are weights matrices of appropriate dimensions and B_1 is a bias vector. The activation function considered was the hyperbolic tangent function $\sigma(\cdot)$ in the hidden layer and the linear function in the output layer. The data of interest to be used for training set is a set of steady state vector consisting of I_{rr}, T_{in}, T_{out} and Q_{in}. Instead of the reference temperature, T_{ref}, the output temperature, T_{out}, was used as the scheduling variable. In fact, assuming a correct behaviour, the output temperature T_{out} converges approximately to the desired temperature T_{ref} in the steady state. According to equation (2) the scheduler actually implements an *inverse* of the plant at steady sate.

The selection of the data set was considered to cover the whole operating range of the plant to as great and extend as possible and the Levenberg-Marquardt was used in the network weights learning stage. As it has been pointed out by Hagan [29] this algorithm is more efficient than other techniques when the network contains no more than a few hundred of parameters, the present situation.

B. Experimental Tuning of the PID controllers

In order to compute the PID parameters several step responses obtained from the available experimental data were used. From the time response three parameters were obtained: the pure time delay L, the rise time T and the static gain K as shown in Figure 3.

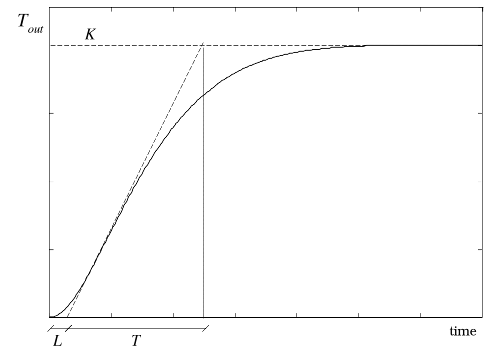


Figure 3. PID tuning with Takahashi rules.

The knowledge of this parameters allows to evaluate the PID parameters q_0, q_1 and q_2 using the discrete Takahashi rules described in Table 1, where T_s defines the sampling time.

	q_0	q_1	q_2
PID	$\frac{T}{L+Ts}$	$2\frac{(L+Ts)^2}{L+Ts}$	$\frac{L+Ts}{2}$

Table 1. PID tuning with discreteTakahashi rules.

This procedure was applied to M different operating points, being the resulting PID controller is describe by

$$Q_{in}(k) = Q_{in}(k-1) + q_0\,e(k) + q_1\,e(k-1) + q_2\,e(k-2) \quad (4)$$

where $e(k)$ is the output error at each discrete time k, defined as

$$e(k) = T_{ref}(k) - T_{out}(k) \quad (5)$$

D. Neural Scheduler Control Structure

A schematic diagram of the proposed neural scheduling PID control is depicted in Figure 4.

The effectiveness of the proposed approach was first tested using a nonlinear distributed parameter model of the Accurex field developed at the University of Sevilla [30]. These simulations were used to further adjust the PID parameters in order to improve the performance of the controllers.

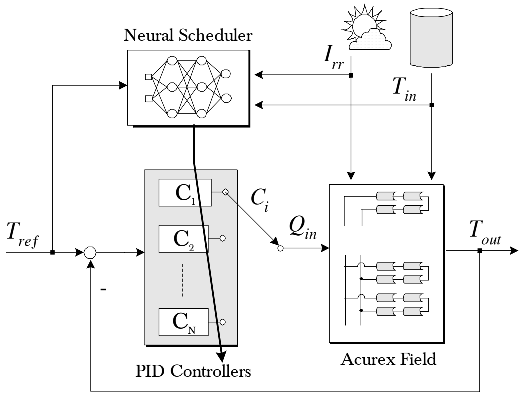


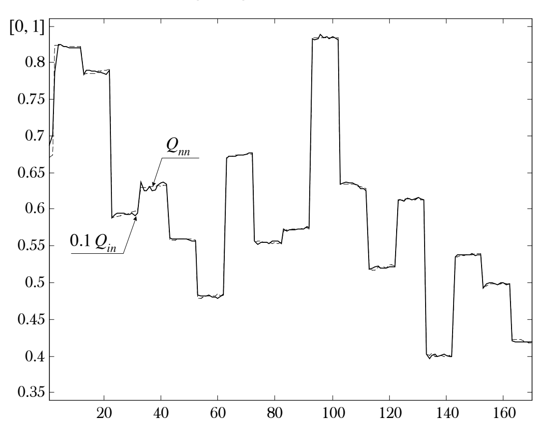
Figure 4. Schematic diagram of neural switching PID control.

IV. APPLICATION TO THE SOLAR POWER PLANT

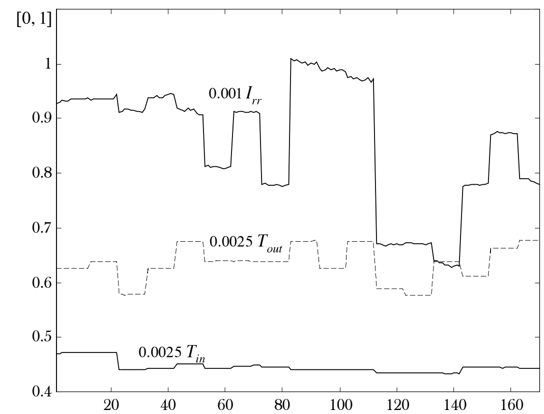
The experiments reported here were conducted on the Accurex Solar Collectors Field of the PSA on 08 and 12 June 2001. The proposed control was implemented in C code and operates over a software developed at PSA [28] also in C code. The sampling time was 15 seconds and the output temperature, T_{out}, was considered as the maximum temperature of all loops.

A. Specification and Training of the Neural Network

To obtain the weights for the neural network a number of test inputs were applied. The number of training patterns, hidden neurons, and input sequence are all chosen by experiments since there is still no reliable method for systematically determining these parameters. It was found that 8 hidden neurons was suitable to obtain a good model for the scheduler. The weights were randomly initialised to a value in $[-0.1, 0.1]$ and, as mentioned, the Levenberg-Marquardt algorithm was applied to evaluate the weights of neural network. In Figure 5 the neural network output is compared with the training target.



(a) Actual output (normalised) versus neural output.



(b) Neural network inputs (normalised).

Figure 5. Training of the neural scheduler.

As can be observed the neural network output Q_{nn} is quite good in describing the desired output good Q_{in}. In fact, the matching between the real and neural output values in some cases is so close that the two lines are almost indistinguishable.

B. Specification and Tuning of PID controllers

The number of local distinct controllers, to be used by the scheduler, was set to $M = 5$, a value established based on the experience acquired from the plant dynamics. The defined regions as well as the PID parameters defined in (4), are presented in Table 2.

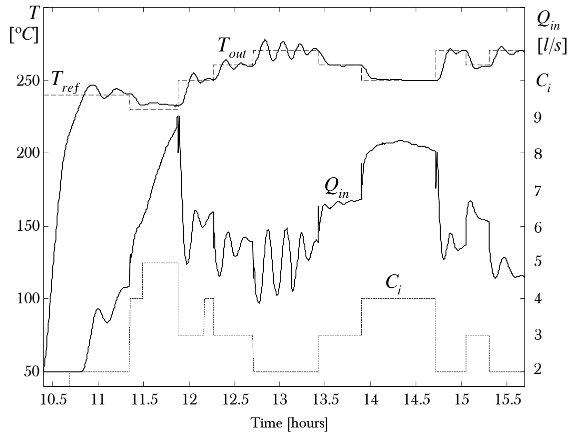
Region	q_0	q_1	q_2
$Q_{in} \leq 3.5$	-0.0875	0.1125	-0.0333
$3.5 < Q_{in} \leq 5.5$	-0.0865	0.1135	-0.0333
$5.5 < Q_{in} \leq 6.5$	-0.2387	0.3613	-0.1333
$6.5 < Q_{in} \leq 8.0$	-0.2075	0.2725	-0.0800
$Q_{in} > 5.5$	-0.0973	0.0947	-0.0107

Table 2. PID parameters.

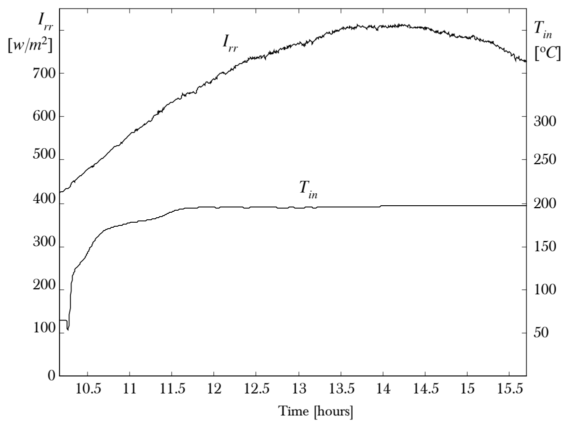
C. Experimental Results

08 June 2001

The first experiment was carried out on 08 June 2001. It was intended to assess the behaviour of the control system at several operation points, by providing different reference temperatures.

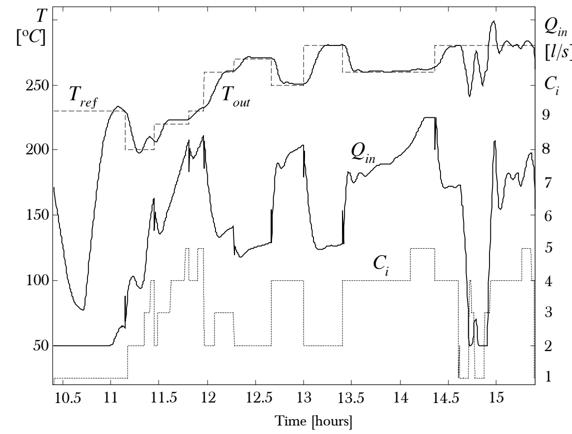


(a) Reference, output temperature, pump flow rate and controller index.

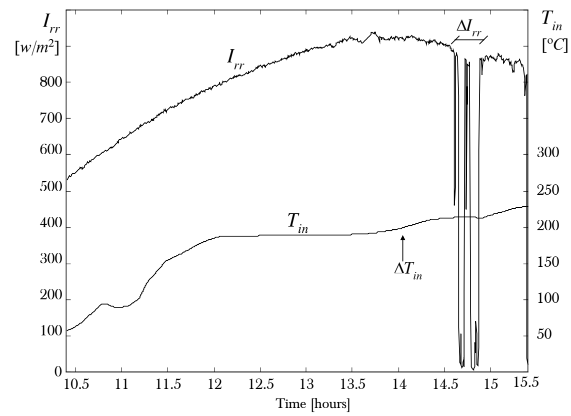


(b) Solar radiation and inlet oil temperature.

Figure 6. Experiment 1: results obtained on 08 June 2001.



(a) Reference, output temperature, pump flow rate and controller index.



(b) Solar radiation and inlet oil temperature.

Figure 7. Experiment 2: results obtained on 12 June 2001.

As can bee seen in Figure 6 the controlled plant behaviour is quite acceptable. The neural network scheduler deals quite well with the different nominal conditions switching to the most suitable controller C_i, as shown in Figure 6(a).

However, as can be observed from Figure 6a, the transient response in the interval $[12.6h, 13.6h]$, corresponding to the controller $C_i = 2$, is not acceptable. This behaviour may be due to a wrong PID parameters or to a incorrect controller selection. Thus, for these operating conditions, either a retuning should be performed or a new controller should be incorporated within the scheduling scheme. The first approach, *i.e.,* the retuning of the controller, was followed and applied again on 12 June.

12 June 2001

The second experiment was carried out on 12 June 2001. Figure 7 shows the results for which several reference temperatures changes were performed. Also, in order to show the rejection capabilities of the proposed control strategy, a change in the inlet oil temperature ΔT_{in}, was intentionally done at instant $14.10h$.

As can bee seen the behaviour is quite good. The response presents almost no oscillations neither overshoot and settles for the new value of the reference temperature in about 15 minutes. The disturbance rejection capabilities of the controller were also acceptable, illustrated by the acceptable behaviour that results from the inlet oil temperature variation.

The effects of strong disturbances, caused by large passing clouds which produce drastic changes in the direct solar radiation level, ΔI_{rr}, were also possible to test. As shown in Figure 6 the behaviour of the control system when intermittent passing clouds occur (at interval $[14.6h, 14.8]$) is acceptable.

V. CONCLUSIONS

A PID based control scheme with a neural network scheduling strategy has been developed and applied to the distributed collector field of a solar power plant. The main purpose was to investigate the use of multiple local linear controllers to cope with changes in the plant dynamic behaviour induced by different operating conditions.

Neural networks are information systems that demonstrate the ability to learn, recall and generalise from training patterns or data. These specific features constitute an advantage to be taken and incorporated in industrial control applications. In this work a neural network was effectively used in the control design of nonlinear systems combined with traditional PID controllers. In this sense neural networks are seen as an extension, rather than replacement, of linear identifiers and controllers that may be already working.

Moreover, the proposed strategy is a systematic one, it can be easily applied to a wide variety of processes with a small initial knowledge of the plant model and the computational requirements of this type of controllers are very acceptable for real time control. Experimental results were reported assessing the feasibility of this control strategy.

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