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Recurrent Neural Networks and Feedback Linearization for a Solar Power Plant Control

P. Gil, J. Henriques and A. Dourado

CISUC - Centro de Informática e Sistemas da Universidade de Coimbra,
Departamento de Engenharia Informática
Pólo II da Universidade, Pinhal de Marrocos, 3030 Coimbra, Portugal
e-mail: {jh, pgil, dourado}@dei.uc.pt, Phone: + 351 239 79 00 00 Fax:+ 351 239 701 266

Abstract
A feedback linearisation control scheme is proposed an implemented on a real solar power plant. This structure is based on a non-linear control methodology combined with a recurrent neural predictor. Given model plant mismatches it is crucial to provide the control system with an off-set compensation, being an internal model controller strategy used for this purpose. Experimental results collected on the solar power plant at Plataforma Solar de Almeria, in south of Spain, illustrate how this methodology can be successfully applied in practice.

1. 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. The main feature of the plant is that its primary energy source, the solar radiation, can not be manipulated by the control system. Moreover, since the solar radiation changes substantially during the plant operation and it is subject to disturbances throughout the daily solar cycle, significant variations in the dynamics will occur. Therefore, it is difficult to obtain a satisfactory control performance over the whole operating range with a sole fixed controller

One possibility to overcome these difficulties is to use adaptive control schemes on the basis of local linear models of the plant, which can mimic changes during the operation, which can be used for self-tuning or within a predictive control framework (Camacho et al, 1994; Pickhardt and Silva, 1998).

The distributed solar collector field is a process where the main disturbances, the solar radiation and the inlet oil temperature, are measurable. Having this in mind, Coito et al (1997) have presented simulation and experimental results concerning the design of a predictive controller (MUSMAR), and Cardoso et al (1999) have proposed a fuzzy supervisor strategy that takes into account this disturbances. Others have suggested intelligent control techniques (Arahal et al, 1997), (Berenguel et al, 1997), (Rubio et al, 1995), (Oksanen and Juuso, 1999). Henriques et al (1999) have suggested a control strategy based on a PID control design with fuzzy logic-switching supervisory. The supervisor is built upon a Takagi-Sugeno fuzzy model to implement an on-line switching between several PID controllers, according to the real time measured conditions. The PID controllers were previously tuned using different models of the plant for specific relevant operating points.

In the past years neural networks (NN) have been attracting a great deal of attention owing to their ability to learn non-linear functions from input-output data examples (Cybenko, 1989).

Concerning control strategies, there are basically two ways in which neural models can be used. In one approach towards the control design the neural network is itself a neural controller and in the other neural networks provide a model to be used in model based control methodologies.

Recurrent neural networks (RNN), introduced by Hopfield (1982) and further developed by other authors (Poznyak et al, 1999), (Kulawski and Brdys, 2000) have some advantages with respect to static NN, in modelling dynamic processes. This type of NN can be used to replace the unknown system, transforming the original control problem into a non-linear control problem suitable to be designed by non-linear control techniques. In this context the geometric approach has provided a variety of tools for the analysis and design of control systems. A well-known technique is the feedback linearisation.

In the present work a feedback linearization based control using a recurrent neural network is investigated. Given the model plant mismatch impossible to eradicate in practice, it is required either to provide an on-line adaptation of the neural networks weights or to incorporate a static offset compensation within the control structure. Here an internal model approach (IMC) scheme was followed. Simulation and experimental results collected from the solar power plant at Almería show the viability and effectiveness of the proposed methodology.

The paper is organised as follows: in the section 2 the proposed NN architecture and the learning algorithm is presented; the feedback linearisation theory is reviewed in section 3; section 4 gives a short description of the solar power plant. In section 5 some simulation and experimental results collected from the solar power plant are presented. Finally, in section 6 some conclusions are drawn.

2. RECURRENT NEURAL NETWORKS

The plant is assumed to be described by the following equations:

$$\begin{aligned} x_p(k+1) &= f\,(\,x_p(k), u(k)\,) \\ y(k) &= C\,x_p(k) \end{aligned} \tag{1}$$

where $f{:}\Re^{n_p}\times\Re^{n_u}\rightarrow\Re^{n_p}$ defines a non-linear function. The vector $x_p\in\Re^{n_p}$ is the state vector (assumed to be unknown and inaccessible), $u\in\Re^{n_u}$ and $y\in\Re^{n_y}$ are, respectively, the process input and output.

2.1 Proposed Recurrent Neural Architecture

Given the approximation capabilities of RNN (Jin et al, 1999) it is assumed that there exist a RNN, described in (2) and shown in Fig. 1, that is able to describe the plant's dynamics.

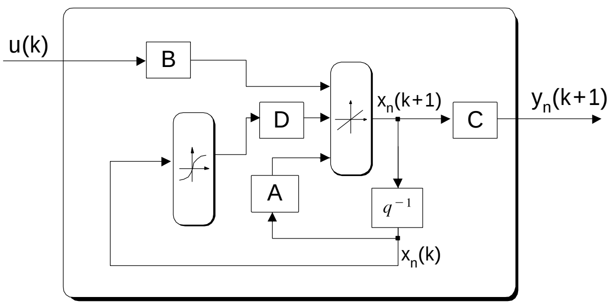


Fig. 1: Recurrent neural network structure.

$$\begin{aligned} x_n(k+1) &= A\,x_n(k) + D\,\sigma(\,x_n(k)\,) + B\,u(k) \\ y_n(k) &= C\,x_n(k) \end{aligned} \tag{2}$$

The vector $x_n\in\Re^n$ is the output of the hidden layer, known as the network hyper-state and $y_n\in\Re^{n_y}$ is the network output. $A\in\Re^{n\times n}$, $B\in\Re^{n\times n_u}$, $C\in\Re^{n_y\times n}$, $D\in\Re^{n\times n}$ are interconnection matrices or weights and the neural activation function $\sigma(\cdot)$ is the hyperbolic tangent function. This architecture can be seen as a modification of the original discrete time RNN proposed by Hopfield, with an additional exogenous input. On the other hand, this architecture can be seen as well as a hybrid model with a linear and a non-linear parts.

2.2 Neural Network Training

With respect to the neural network's weights estimation, as pointed out by Hagan and Menhaj (1994), the Levenberg-Marquardt is more efficient than other techniques when the network contains no more than a few hundred parameters. Due to its effectiveness this algorithm has been applied for the off-line training of RNN's. According to this algorithm, the neural network weights are updated iteratively as follows:

$$\Delta W = -(H + \lambda\,I\,)^{-1}\,\nabla J(W) \tag{3}$$

where H denotes de Hessian of the cost function $J(w)$, $\nabla J(w)$ is the gradient and λ is the Marquardt coefficient. The Levenberg-Marquardt algorithm has a very attractive feature has it spans from a steepest descent type method for large values of λ, to a Gauss-Newton method for $\lambda\rightarrow 0$. A straightforward strategy for selecting λ is proposed in Hagan and Menhaj (1994).

3. FEEDBACK LINEARIZATION

Linearization by feedback is a well-established approach to the control of non-linear systems. The main idea is to transform a non-linear state space model of the plant into to new coordinates system where the non-linearities can be cancelled by feedback. In this context the aim of feedback linearisation is cancelling the non-linearities of the system and imposing a desired linear dynamics.

Here the unknown system is described by a non-linear state space neural network model.

3.1 Problem Formulation

Given the plant described by (2), assume the following relationships:

$$\Delta x_n(k+1) = x_n(k+1) - x_n(k) \tag{4}$$

$$\Delta u(k) = u(k) - u(k-1) \tag{5}$$

$$\Delta\sigma(x_n(k+1)) = \sigma(x_n(k+1)) - \sigma(x_n(k)) \tag{6}$$

By using the above expressions follows:

$$\Delta x_n(k+1) = A\,\Delta x_n(k) + B\,\Delta u(k) \;+\; D\,\Delta\sigma(x_n(k)) \tag{7}$$

The increment $\Delta y(k)$ is defined by:

$$\Delta y_n(k+1) = \; y_n(k+1) - y_n(k) \tag{8}$$

$$\Delta y_n(k+1) = CA\,\Delta x_n(k) + CB\,\Delta u(k) + CD\,\Delta\sigma(x_n(k+1)) \tag{9}$$

From (8) follows:

$$CB\,\Delta u(k) = \;\Delta y_n(k+1) - CA\,\Delta x_n(k) - CD\,\Delta\sigma(x_n(k+1)) \tag{10}$$

Then,

$$\Delta u(k) = \;(CB)^{-1}\,[\;\Delta y_n(k+1) - CA\,\Delta x_n(k) \\ - CD\,\Delta\sigma(x_n(k))\;] \tag{11}$$

and finally the control action can be given by:

$$u(k) \;\;=\;\; u(k-1) \;+\; \Delta u(k) \tag{12}$$

In equation (8) since the term $y_n(k+1)$ is unknown it is replaced by the reference signal at instant $k+1$, $y_d(k+1)$. Thus, by this means, the non-linearities of the neural network model are appropriately cancelled in order to obtain a linear input-output mapping. As a result, the control structure incorporates an integral action, which enables in theory a free steady state off-set for the model description.

As the cancellation is not exact for the solar plant due to modelling uncertainties an internal model control scheme is incorporated within the feedback linearisation control framework, as shown in Fig. 2.

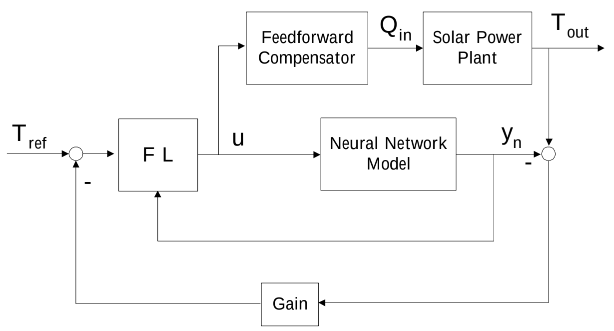


Fig. 2: Control structure.

4. THE SOLAR POWER PLANT

The Acurex distributed solar collector field at Plataforma Solar de Almería (PSA) is quite well described in literature (Kaltz, 1982; Camacho et al, 1992) and is located at the desert of Tabernas, in south of Spain. 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. The plant is able to provide 1.2 MW peak of thermal power. A schematic diagram is shown in Fig. 3.

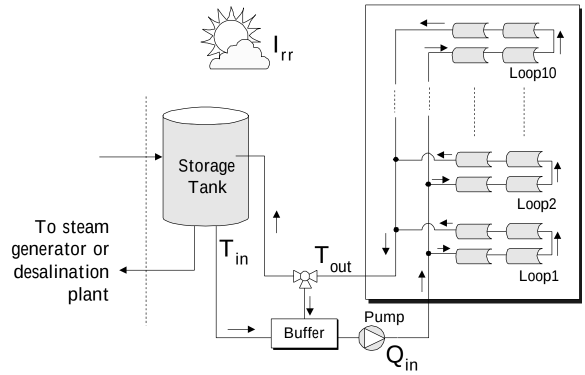


Fig. 3: Schematic diagram of the Acurex field.

Each collector uses parabolic mirrors to concentrate the radiation in a receiver tube. Synthetic oil is pumped through the receiver tube and picks up the heat transferred through the tube walls. The cold inlet oil is collected from the storage tank and is pumped through the field. The heated fluid is introduced into the storage tank to be used for electrical energy generation or feeding a heat exchanger of the desalination plant. The manipulated variable in the plant is the oil flow rate Q_{in}, being the main goal to drive the outlet field oil temperature T_{out} to a prescribed value T_{ref}. The main disturbances are the solar radiation I_{rr} and the inlet oil temperature T_{in}.

5. RESULTS

Experiments were carried out on the Acurex solar collector field of the Plataforma Solar de Almería on 13 June 2001. The proposed control scheme was implemented in C code and linked within a software package developed at PSA (López, 1996), also in C code. In order to assess the feasibility of the proposed control scheme simulations were first carried out using the model developed at the University of Sevilla (Berenguel et al, 1993).

5.1 Neural Network Training

The distributed solar collector field is a process where the main disturbances, the solar radiation and the inlet oil temperature, are measurable. Therefore, it makes sense to incorporate this knowledge in the design of a feedforward compensator, which has shown interesting properties. In the present work the relation (13), characterising the steady state behaviour, was used.

$$Q_{in} = \frac{11423 \times 10^2 I_{rr}}{(903 - 0.67\, T_{ref})\,(1820 + 3.47\, T_{ref})\,(T_{out} - T_{in})} \qquad (13)$$

A schematic diagram of the compensator is presented in Fig. 4.

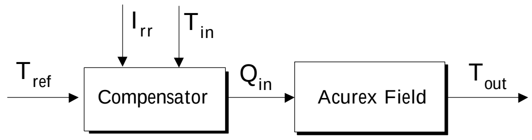


Fig. 4: Feedforward compensator.

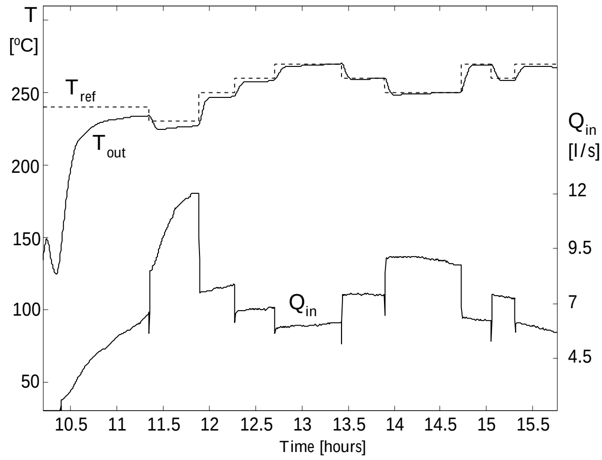
To obtain an initial estimation of the neural network parameters a number of inputs were fed to the plant. The goal in designing the test inputs was to cover the operating range of the plant to as great and extend as possible. By a trial and error approach it was found that a selection of two hidden neurons, $n = 2$, is quite suitable to provide a good model for the Acurex plant.

The network training was performed via the Levenberg-Marquardt algorithm, considering that input and output data were appropriately scaled.

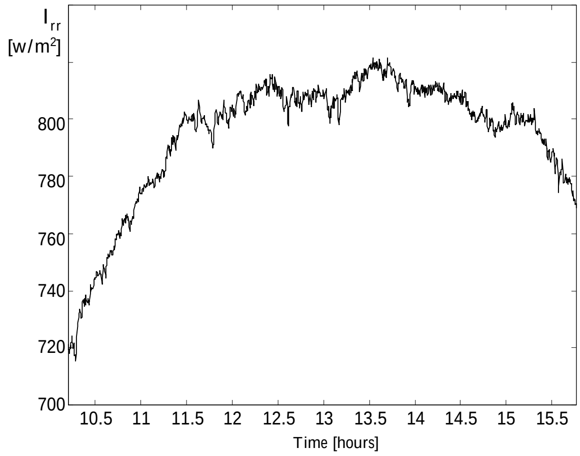
5.2 Simulation Results

Simulations were carried out in view of two main goals. On one hand, to assess the global performance of the control scheme in a wide range of operating conditions, and on the other hand to support the tuning of the control parameters.

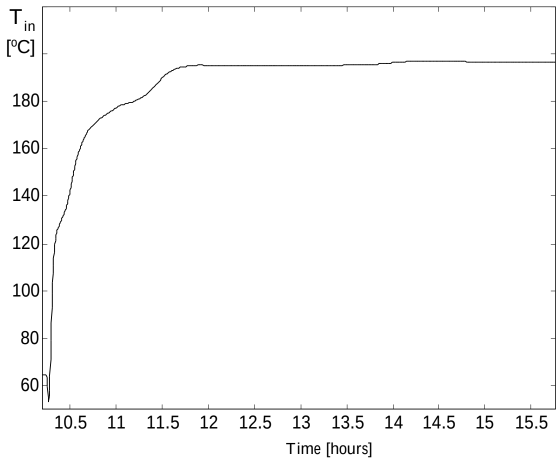
From the results shown in Fig. 5, it can be seen that the proposed strategy is able to perform fairly well in different nominal operating conditions. In the simulations were used the data collected on 8 June 2001 (climacteric data and the oil temperature).



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



(b) Solar radiation.



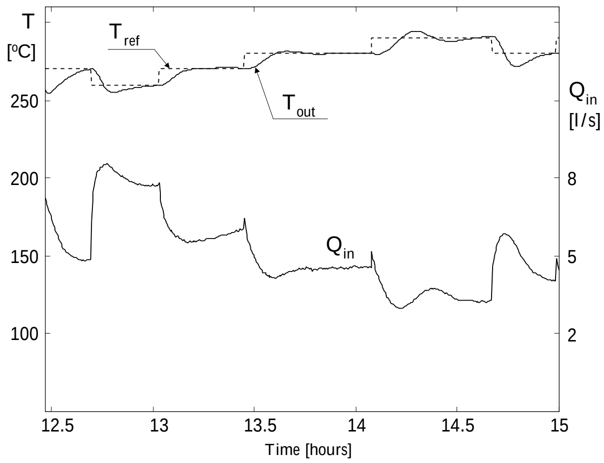
(b) Inlet oil temperature.

Fig. 5: Simulation results.

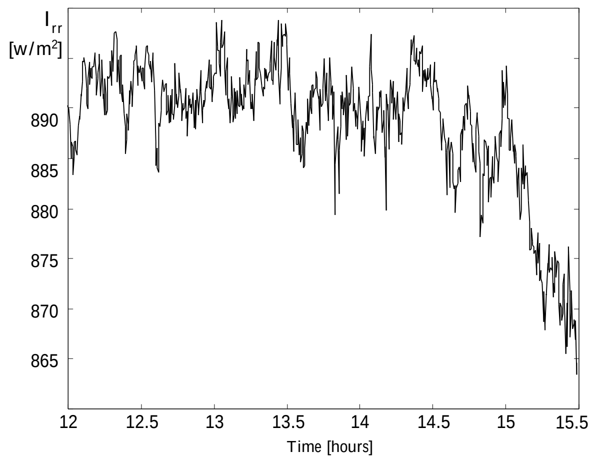
5.3 Experimental Results

The experiments on the Solar Power Plant were carried out on 13 June 2001. The sampling time was chosen as 15 seconds and the output temperature (T_{out}) was considered as the maximum oil temperature for the active loops.

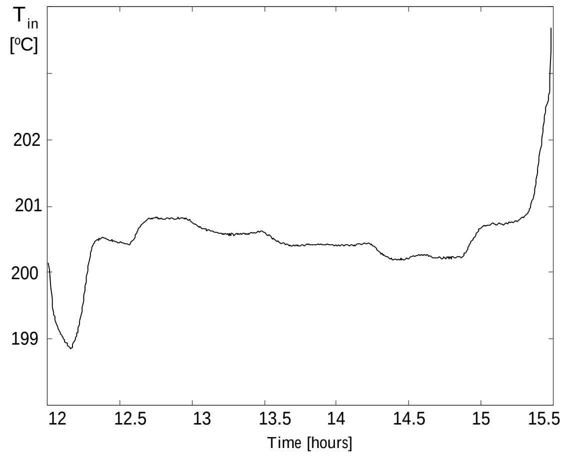
As can bee seen, in Fig. 6 the control system output is stable and the deviation from the set-points is not significant.



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



(b) Solar radiation.



(b) Inlet oil temperature.

Fig. 6: Experimental results obtained on 13 June 2001.

6. CONCLUSIONS

A feedback linearisation control scheme based on a recurrent neural network was implemented in real-time and applied to a distributed collector field of a solar power plant. The proposed strategy is a systematic one, which can be readily applied to a wide variety of processes without having to know in advance the first principle model of the plant. To cope with the plant/model mismatches an IMC approach was designed and incorporated within the control scheme.

Experimental results confirm the simulation results and show that the system has robustness with respect to changes in solar radiation, inlet oil temperature and operating conditions. This experimental study has shown that neural networks are an important methodology for many industrial control applications. The simplicity and reliability of neuro-control presents a high potential for the development of efficient and intelligent control systems.

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