ELSEVIER International Journal of Approximate Reasoning 22 (1999) 73–91

INTERNATIONAL JOURNAL OF APPROXIMATE REASONING

Supervision and c-Means clustering of PID controllers for a solar power plant

Jorge Henriques [*,1], Alberto Cardoso [2], António Dourado [3]

CISUC, Centro de Informática e Sistemas da Universidade de Coimbra, Departamento de Engenharia Informática, Pólo II, UC 3030 Coimbra, Portugal

Received 1 October 1998; accepted 1 February 1999

Abstract

A hierarchical control strategy consisting on a supervisory switching of PID controllers, simplified using the c-Means clustering technique, is developed and applied to the distributed collector field of a solar power plant. The main characteristic of this solar plant is that the primary energy source, the solar radiation, cannot be manipulated. It varies throughout the day, causing changes in plant dynamics conducting to distinct several operating points. To guarantee good performances in all operating points, a local PID controller is tuned to each operating point and a supervisory strategy is proposed and applied to switch among these controllers accordingly to the actual measured conditions. Each PID controller has been tuned off-line, by the combination of a dynamic recurrent non-linear neural network model with a pole placement control design. To reduce the number of local controllers, to be selected by the supervisor, a c-Means clustering technique was used. Simulation and experimental results, obtained at Plataforma Solar de Almería, Spain, are presented showing the effectiveness of the proposed approach. © 1999 Elsevier Science Inc. All rights reserved.

[*] Tel.: +351-39-790000; fax: +351-39-701266; e-mail: jh@dei.uc.pt

[1] The experiments were carried out within the project "Innovative Training Horizons in Applied Solar Thermal and Chemical Technologies" (C. N.:ERBFMGECT950023) supported by the European Union Program "Training and Mobility of Researchers" and promoted by CIEMAT-IER. The authors would like to express their gratitude to the personnel of the Plataforma Solar de Almeria, in particular Pedro Balsa. The authors also acknowledge suggestions by the reviewers that have helped considerably in the improving of this paper. This work was partially supported by the Portuguese Ministry of Science and Technology (MCT), under program PRAXIS XXI.

[2] E-mail: alberto@dei.uc.pt

[3] E-mail: dourado@dei.uc.pt

PII: S0888-613X(99)00017-1

Keywords: Fuzzy supervisor; Clustering; Switching control; PID control; Neural networks; Solar power plants

1. Introduction

The main control requirement in a solar power plant, in order to be able to use the heated oil for power production, is to maintain the outlet oil temperature from the collector field at a constant pre-specified value. The fundamental feature of the plant is that its primary energy source, the solar radiation, is a measurable disturbance and cannot be influenced by the control system. Moreover, since the solar radiation changes substantially during plant operation, due to the daily solar cycle, atmospheric conditions, such as a cloud cover, humidity and turbidity, this leads to significant variations in the dynamic characteristics (e.g., the time constant and the time delay) of the field, corresponding to different operation conditions. Therefore, it is difficult to obtain a satisfactory performance over the total operating range with a static controller.

This paper presents the application of a hierarchical control strategy to the distributed collector field of a solar power plant at the Plataforma Solar de Almería. The Acurex distributed solar collector field of this solar plant is well described in literature [6,7] and is located at 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 picture and a schematic diagram are shown, respectively, in Figs. 1 and 2.

Each collector uses parabolic mirrors to concentrate solar radiation in a receiver tube. Synthetic oil is pumped through the receiver tube and picks up the heat transferred through the tube walls. The inlet oil, at temperature T_{in}, is pumped from the bottom of the storage tank flowing through the collector field where its temperature is raised. Next, the heated fluid is introduced into the storage tank, from the top, to be used for electrical energy generation or feeding a heat exchanger in the desalination plant. The manipulated variable in the solar plant is the oil flow rate, Q_{in}, and the main goal is 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.

To deal with the several operating points, that characterises the plant behaviour, some control strategies have been proposed. One of them applies adaptive control schemes, using local linear models of the plant, which mimic changes during the operation [7,5]. In Ref. [8], experimental results when measurable disturbances of the plant (solar radiation and inlet oil temperature)

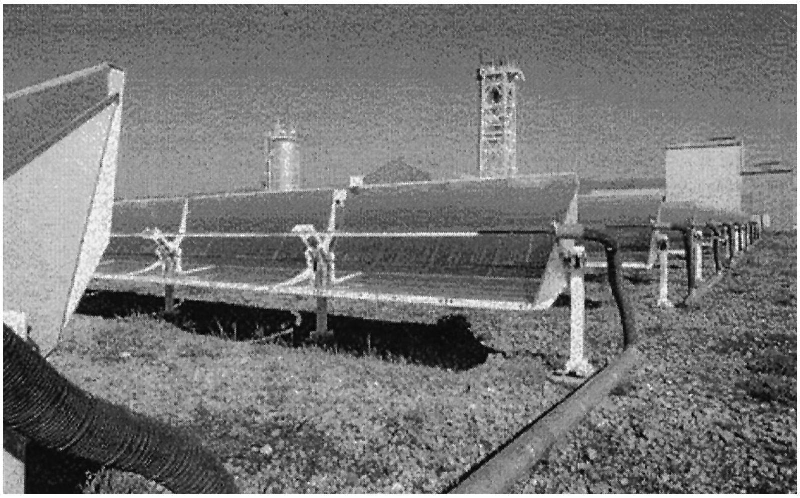

Fig. 1. Acurex solar collector field.

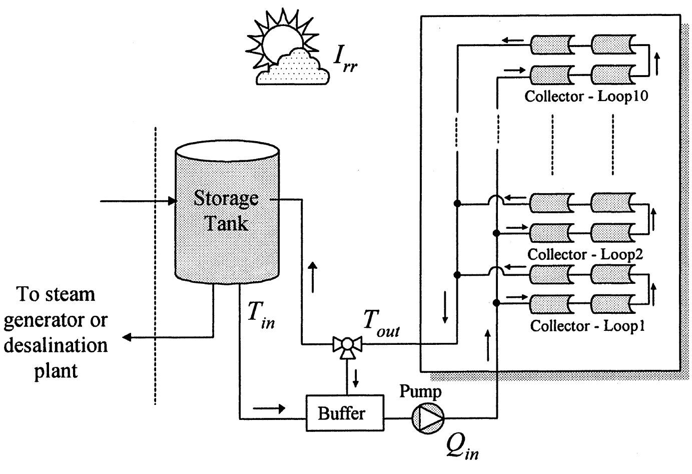

Fig. 2. Schematic diagram of the Acurex field.

are included in the design of a predictive MUSMAR-controller, are presented. Also fuzzy controllers (e.g., incremental PI fuzzy controller) have been tested at this plant [21,3]. In some of these contributions a feedforward compensation term, obtained from the static behaviour of the plant, has been proposed to compensate the effects of the radiation and the difference between the desired output temperature and the inlet temperature. Another possibility is to apply an indirect adaptive controller, using a certain predictive search strategy based on a mathematical model of the process [19,18]. Another alternative might be the commissioning of a switching controller using different models of the plant for different operating points [20]. A similar strategy has been followed in this work.

There are several ways to design a controller for each local model. Traditional PID controllers have some well known advantages, such as the dynamic performance reached in some nominal operating conditions, reliability based on stability studies and their industrial widespread use [9]. They are simple to implement and have been succeeded in regulating many industrial processes.

In order to improve the performance of PID controllers, several strategies have been proposed, such as adaptive or supervising techniques. One can consider the following main reasons for using a supervisor [12]:

(i) adaptive controllers are able to cope with most of the cases that leave the PID under-optimal, but they require specialised design methods using some a priori model structure knowledge [16];

(ii) PID supervisors are easier to implement because they need very little knowledge about the process;

(iii) the combination of a linear PID control law with a supervisory strategy can lead to a highly non-linear control law; then it can allow increasing significantly the robustness of the control system [1];

(iv) finally, the supervisor can provide an interface with the user for expressing precisely the specifications in terms of close loop performances.

One possibility to implement the supervisor is using the fuzzy logic methodology (some examples are described in Ref. [13]). Fuzzy logic, [23], has been considered as an effective tool to deal with disturbances and uncertainties in terms of vagueness, ignorance and imprecision.

In this work the hierarchical control strategy is based on a PID control technique with a fuzzy logic switching supervisor. The supervisor has been derived using a fuzzy method to implement on-line the switching between each PID controller, accordingly to the measured conditions. The local PID controllers have been previously tuned off-line using a neural network approach, that combines a dynamic recurrent non-linear neural network model with a pole placement control design. For reducing the number of local controllers, a c-Means clustering technique was applied.

The paper is organised as follows. Section 2 describes the neural network approach to design the PID controllers and the classification technique is presented. The fuzzy switching supervisory, providing the mechanism to switch between the PID controllers, is also described. In Section 3 some simulations and experimental results are presented. Finally, some conclusions are embodied in Section 4.

2. Control methodology

2.1. PID design and tuning

Neural networks have been successfully applied for the modelling and control of non-linear systems. The dynamic recurrent neural networks, which involve dynamic elements and feedback connections, have been considered more suitable for modelling dynamical systems [11]. In this work, a recurrent Elman's neural network was used to obtain each nominal model. The corresponding nominal parameters of each PID controller were obtained with a pole placement algorithm, assuming a linearisation of each nominal neural model. Additionally, in order to improve the controllers performance, the experience acquired from the plant behaviour can be used to further adjust the PID parameters.

For the controller design, the available plant data, obtained by experimental results from other researchers, was used. Due to the difficulty to obtain data covering all range of possible operating conditions, some controllers were designed using data from a simulation plant model [2]. In this case the following relation [2], characterising the steady state behaviour, was used

$$Q_{\mathrm{in}} = \frac{0.7869\, I_{\mathrm{rr}} - 0.485(T_{\mathrm{out}} - 151.5) - 80.7}{T_{\mathrm{out}} - T_{\mathrm{in}}}. \tag{1}$$

It is assumed that each nominal model is described by a general non-linear discrete state equation in the form

$$x(k) = f\{x(k-1), Q_{\mathrm{in}}(k-1)\}, \tag{2}$$

$$T_{\mathrm{out}}(k) = h\{x(k)\}, \tag{3}$$

where f and h are non-linear functions and $x(k) \in \Re^n$ represents a state vector, at discrete time k. The ability of a recurrent Elman's network to approximate a discrete time non-linear system is used [17]. No previously assumptions are made about the process, with the exception that the maximum value for its order (n) is known in advance. An Elman's network can be described by the following equations:

$$x^{\mathrm{h}}(k) = \sigma\{W^{xc}x^{\mathrm{c}}(k), W^{xu}Q_{\mathrm{in}}(k-1)\}, \tag{4}$$

$$x^{\mathrm{c}}(k) = \lambda x^{\mathrm{c}}(k-1) + x^{\mathrm{h}}(k-1), \tag{5}$$

$$T_{\mathrm{out}}(k) = W^{yx}x^{\mathrm{h}}(k), \tag{6}$$

where $\sigma\{\cdot\}$ is a hyperbolic tangent non-linear function, $x^{\mathrm{c}}(k)$ is a context unit and $x^{\mathrm{h}}(k)$ is a hidden unit. The context units are locally recurrent and a multiplicative constant, λ, decreases the values as they are fed back. This constant determines the memory depth, i.e., how long a given value fed to the context unit will be remembered. The interconnection matrices, $W^{xu} \in \Re^{n,1}$, $W^{xc} \in \Re^{n,n}$ and $W^{yx} \in \Re^{1,n}$ which define the interconnection paths for the context-hidden layer, input-hidden layer and hidden-output layer, respectively, are evaluated from the truncated Werbos' backpropagation through time algorithm [22]. Due to the computational complexity of the BTT, a natural simplification was obtained by truncating the backpropagation of the information to a fixed number of prior time steps, on a sliding window mode. From the non-linear neural model, Eqs. (4)–(6), it is possible to derive a linear model by computing the derivatives from the output (T_{out}) with respect to the input (T_{in}), extracting the actual linearised parameters [10]. Following this approach a discrete time, linear time invariant (LTI), single input single output (SISO) system can be obtained in the form of a standard discrete time state space model:

$$x(k) = W^A x(k-1) + W^B Q_{in}(k-1), \tag{7}$$

$$T_{out}(k) = W^C x(k). \tag{8}$$

W^A, W^B and W^C are matrices of dimension (n, n), $(n, 1)$ and $(1, n)$, respectively. Due to the identifiability of the controller parameters, a second order system ($n = 2$) was considered. Adopting an input-output representation, the system described by Eqs. (7) and (8) can be defined by

$$P(q^{-1}) = \frac{B(q^{-1})}{A(q^{-1})} = \frac{T_{out}(q^{-1})}{Q_{in}(q^{-1})} = \frac{b_1 q^{-1} + b_2 q^{-2}}{1 + a_1 q^{-1} + a_2 q^{-2}}, \tag{9}$$

where q^{-1} is the backward shift operator. Concerning the PID controller, it is defined by

$$F(q^{-1}) Q_{in}(k) = G(q^{-1}) e(k). \tag{10}$$

The output error, $e(k)$, is defined as the difference between the desired outlet oil temperature, T_{ref}, and the actual outlet oil temperature, T_{out}.

$$e(k) = T_{ref}(k) - T_{out}(k). \tag{11}$$

$F(q^{-1})$ and $G(q^{-1})$ are polynomials in the form

$$F(q^{-1}) = 1 + f_1 q^{-1} + f_2 q^{-2} = \left(1 - q^{-1}\right)\left(1 + f q^{-1}\right), \tag{12}$$

$$G(q^{-1}) = g_0 + g_1 q^{-1} + g_2 q^{-2}. \tag{13}$$

The resulting closed loop transfer function is given by

$$T_{out}(k) = \frac{BG(q^{-1})}{AF(q^{-1}) + BG(q^{-1})} T_{ref}(k). \tag{14}$$

The PID polynomials are computed such that the closed loop poles, obtained from the solution of Diophantine equation (15), are placed in the desired locations p_1 and p_2.

$$AF(q^{-1}) + BG(q^{-1}) = A_m(q^{-1}), \tag{15}$$

$$A_m(q^{-1}) = \left(1 - p_1 q^{-1}\right)\left(1 - p_2 q^{-1}\right) = 1 + \gamma_1 q^{-1} + \gamma_2 q^{-2}. \tag{16}$$

Finally, the PID parameters are evaluated by the following equation:

$$\Theta = \Gamma^{-1}\Omega, \tag{17}$$

where Θ, Γ and Ω are matrices defined by

$$\Theta = \begin{bmatrix} f_1 \\ f_2 \\ g_0 \\ g_1 \\ g_2 \end{bmatrix}, \tag{18}$$

$$\Gamma = \begin{bmatrix} 1 & 0 & b_1 & 0 & 0 \\ a_1 & 1 & b_2 & b_1 & 0 \\ a_2 & a_1 & 0 & b_2 & b_1 \\ 0 & a_2 & 0 & 0 & b_2 \\ 1 & 1 & 0 & 0 & 0 \end{bmatrix}, \tag{19}$$

$$\Omega = \begin{bmatrix} \gamma_1 - a_1 \\ \gamma_2 - a_2 \\ 0 \\ 0 \\ -1 \end{bmatrix}. \tag{20}$$

2.2. Supervisor design

To formulate the design problem it is assumed that it is possible to represent the plant dynamics by a number of characteristics behaviours $M_1, M_2, \ldots, M_N$ and that, for each M_i, a corresponding model P_i may be derived, where each P_i is called a nominal model. In order to obtain a desired performance when the plant is operating under conditions M_i, it is assumed that a nominal controller C_i, can also be designed. The hierarchical control structure, which is based on a fuzzy switching supervisor of PID controllers, is shown in Fig. 3.

The fuzzy supervisor consists of three stages: the fuzzification, the fuzzy rule inference and the defuzzification. The first one converts the numerical values of the solar radiation (I_{rr}) and the reference temperature (T_{ref}) defining the nominal operating points into linguistic variables. The fuzzy rule base defines the switching control strategy. The selected controller is obtained by the defuzzification part, which chooses among rules that have been fired simultaneously.

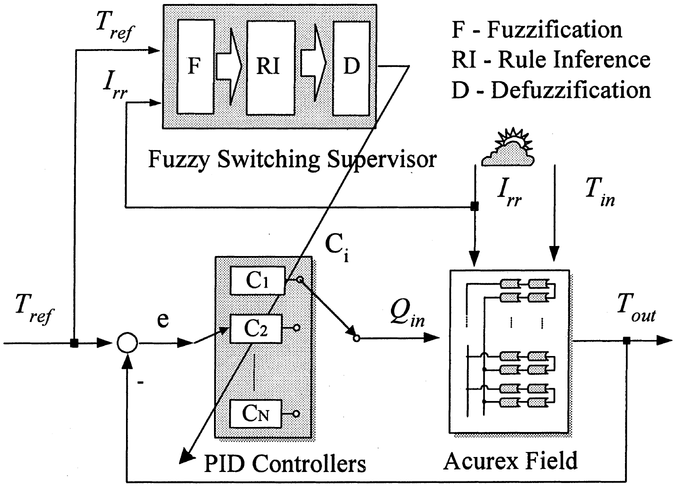

Fig. 3. Diagram of the fuzzy switching supervisor PID control.

An intuitive method, issued from the knowledge of the operators and the authors themselves, was used to derive the membership functions for the linguistic variables, solar radiation and reference temperature. The universes of discourse I and R, respectively, for the solar radiation and reference temperature, were defined by

$$I \equiv \left[600\ \mathrm{W/m^2}, 1000\ \mathrm{W/m^2}\right], \tag{21}$$

$$R \equiv [230°\mathrm{C}, 270°\mathrm{C}]. \tag{22}$$

For both variables five linguistic terms were assumed

$$\{VS, SM, NO, LA, VL\} = \{VerySmall, Small, Normal, Large, VeryLarge\}. \tag{23}$$

The fuzzy sets, SI and SR, are defined as a set of ordered pairs:

$$SI = \{(I_{\mathrm{rr}}, \mu_I(I_{\mathrm{rr}})) \mid I_{\mathrm{rr}} \in I\}, \tag{24}$$

$$SR = \{(T_{\mathrm{ref}}, \mu_R(T_{\mathrm{ref}})) \mid T_{\mathrm{ref}} \in R\}. \tag{25}$$

The membership functions, $\mu_I(I_{\mathrm{rr}})$ and $\mu_R(T_{\mathrm{ref}})$, respectively, for the solar radiation and the reference temperature, were considered triangular, as shown in Figs. 4 and 5.

The rule base that defines the strategy to switch between controllers is drawn in table of Fig. 6. The two rule base inputs, assuming to describe the actual nominal conditions, are the solar radiation and reference temperature. The output $i = 1, \ldots, 25$ is the index that identifies the selected controller, C_i.

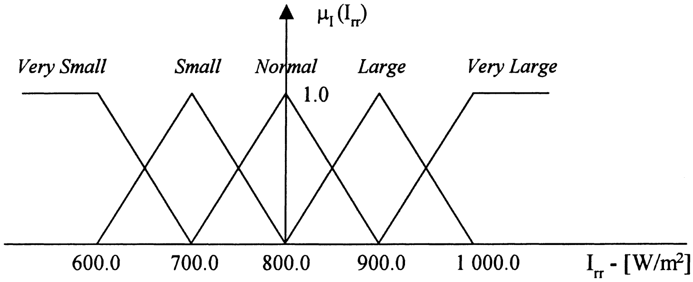

Fig. 4. Solar radiation membership function.

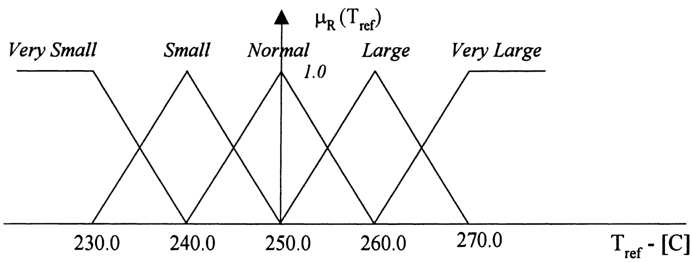

Fig. 5. Reference temperature membership function.

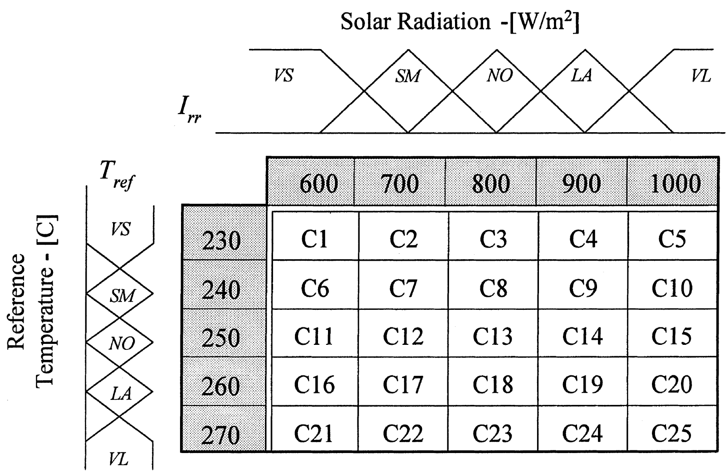

Fig. 6. Switching supervisor rule base.

In general a Mamdani fuzzy system [15] is described by a set of rules in the form

$$\text{Rule } i: \quad \begin{array}{l} \text{IF } (x \text{ is } X) \text{ AND } (y \text{ is } Y) \\ \text{THEN } (z \text{ is } Z), \end{array} \tag{26}$$

where X and Y are fuzzy sets in the antecedent and Z is a fuzzy set in the consequent. In a Mamdani type inference, after the aggregation process, it is common to have a fuzzy set for each output variable that needs defuzzification. However, it is possible to use a singleton as the output membership function rather than a fuzzy set. Following this idea the switching supervisor rule base (table shown in Fig. 6 can be described by a set of rules in the following way

$$\begin{aligned} \text{Rule } i: \quad & \text{IF } \left(I_{\text{rr}} \text{ is } SI^{(i)}\right) \text{ AND } \left(T_{\text{ref}} \text{ is } SR^{(i)}\right) \\ & \text{THEN } \alpha_i = \mu_I^{(i)}(I_{\text{rr}}) \otimes \mu_R^{(i)}(T_{\text{ref}}), \end{aligned} \tag{27}$$

where $SI^{(i)}$ and $SR^{(i)}$ define, respectively, the linguistic values of variables I_{rr} and T_{ref} for the ith rule, $i = 1, \ldots, 25$, $\mu_I^{(i)}(I_{\text{rr}})$ and $\mu_R^{(i)}(T_{\text{ref}})$ define the respective membership degrees and $\otimes$ denotes the common *product* operator.

The aggregation of the consequents of the fired rules, determine i such that $\alpha_i = \alpha_{\max} = \max\{\alpha_1, \ldots, \alpha_{25}\}$. This index identifies the controller to be selected. This very simple procedure has proved to be effective.

Usually only one controller will be active. In the case that two controllers were simultaneously activated, it is assumed that the rule which correspond to the highest reference temperature membership function, $\mu_R^{(i)}(T_{\text{ref}})$, will be the selected one and the corresponding controller is selected for control purposes.

Fig. 7 shows the fuzzy switching approach for a particular situation ($I_{\text{rr}} = 620$ W/m^2 and $T_{\text{ref}} = 267°$C). Using the proposed fuzzy model, the selected controller was the C_{21}.

2.3. Clustering and supervisor simplification

The purpose of clustering is to classify a data set $D = \{d_1, d_2, \ldots, d_N\}$ into homogeneous groups of data $V = \{v_1, v_2, \ldots, v_M\}$ with $1 \leqslant M \leqslant N$ (if $M = 1$, all data belongs to the same class and if $M = N$, each data sample defines a class). The c-Means clustering algorithm [4] is an extremely powerful classification method which minimises the Euclidean distance between each data point (controller coefficients) and its cluster center. The number of clusters (M) should reflect the level of knowledge of the system under consideration, or the level of generality in the user's description of the system.

In this work the data to be classified are the parameters of the nominal PID controllers $C_i, i = 1, \ldots, 25$ (which can be interpreted as 3D points, see Fig. 8). Seven clusters (distinct controller classes) were considered, $M = 7$. After applying the c-Means clustering procedure, the initial 25 controllers (symbol + in Fig. 8) were reduced to seven classes (symbol O in Fig. 8).

By reducing the number of controllers, the task of re-tuning of the nominal controllers can be simplified. The final rule base, which defines the supervision task, is now presented in table of Fig. 9.

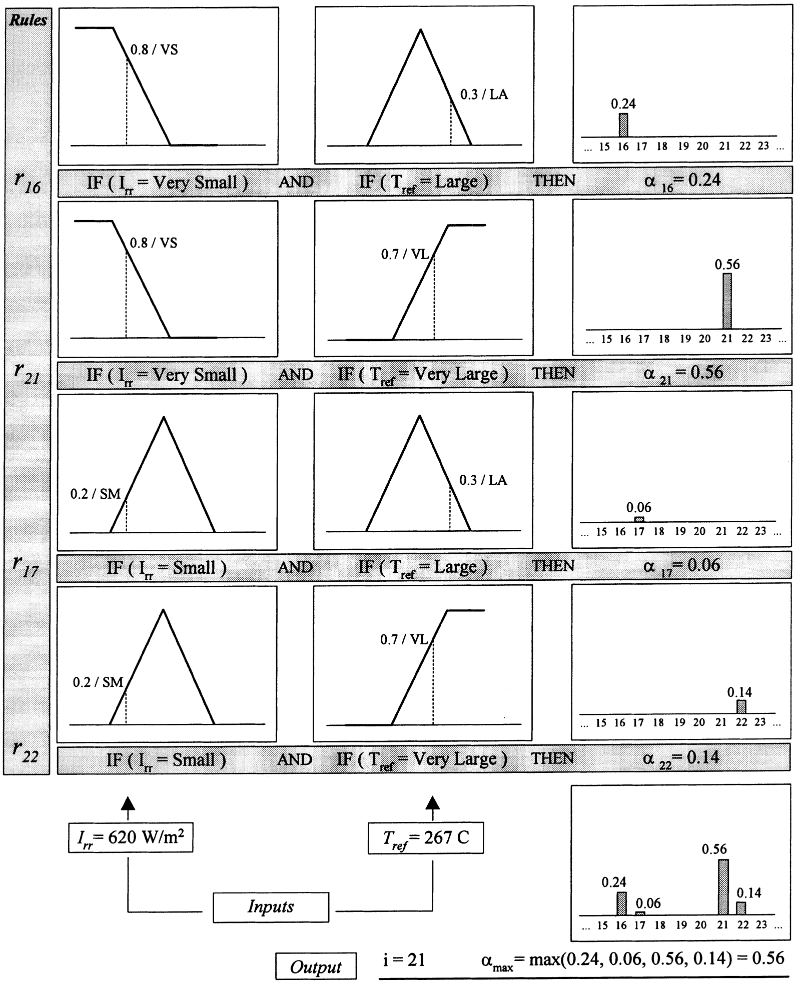

Fig. 7. Example of the fuzzy inference mechanism.

3. Results

The experiments were carried out in the Acurex solar collectors field of the Plataforma Solar de Almería from 6 to 7 July 1998. The proposed control was implemented in C code and operates over a software developed at PSA [14], also in C code. The effectiveness of the developed approach was first tested in simulation using a non-linear distributed parameter model of the Acurex field, developed at the University of Sevilla [2]. Also, a comparison between the

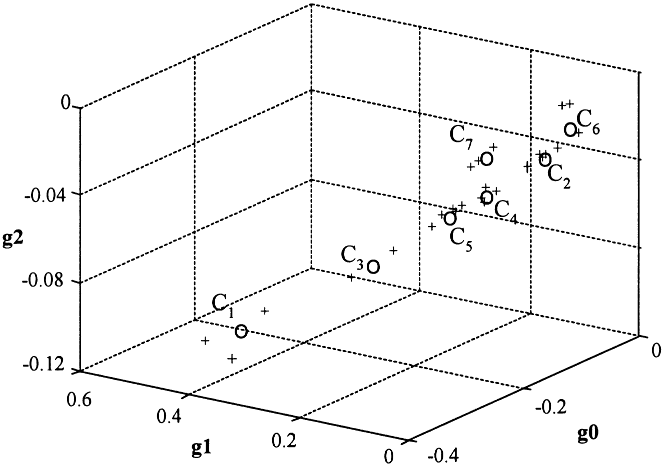

Fig. 8. Clustering of the PID controllers (+:- initial controllers; O:- final controllers).

Reference Temperature -[C] \ Solar Radiation -[W/m²]	600	700	800	900	1000
230	C5	C5	C2	C6	C6
240	C5	C1	C5	C2	C2
250	C7	C5	C1	C4	C2
260	C7	C2	C4	C3	C4
270	C6	C7	C1	C4	C3

Fig. 9. Simplified supervisor rule base.

behaviour of the proposed approach with the behaviour of a fixed PID controller was performed.

The described experiments intended to show the results in the following situations: (i) several changes in the operating points, by setting different reference temperatures (it is not possible to manipulate the solar radiation) and (ii) the rejection capabilities of the controller to disturbances in the inlet oil temperature and when the addition/suppression of a collector loop from operation was done.

The effect of strong disturbances caused by large passing clouds, which produce drastic changes in the direct solar radiation level, was not possible to test due to the clear conditions during the experiments. In all the experiments the sampling time was 15 s and the output temperature (T_{out}) was considered as the average temperature of the all loops (another typical strategy is to assume the maximum value).

3.1. Simulations

The performance of the proposed strategy was compared with a static PID controller. This controller was designed for the operating point, $I_{rr} = 800$ W/m^2 and $T_{ref} = 240$°C, in other words, the controller C_5 was implemented. The data used to perform the present simulation (T_{in} and I_{rr}) was obtained on 6 July 1998 (the solar radiation evolution is presented in Fig. 12).

From the simulation results (Fig. 10) it can be seen that the fixed PID controller is well designed for its nominal conditions (approximately from 10 h 10 min to 10 h 50 min, from 12 h 15 min to 12 h 50 min and from 14 h 10 min to the end of the time simulation), but for other conditions the performance deteriorates.

The proposed strategy, on the other hand, deals quite well with these nominal conditions variations, providing significant improvements in the performance of the closed loop system (Fig. 11). The selected controller, computed by the fuzzy supervisor, and the solar radiation evolution, are shown in Fig. 12.

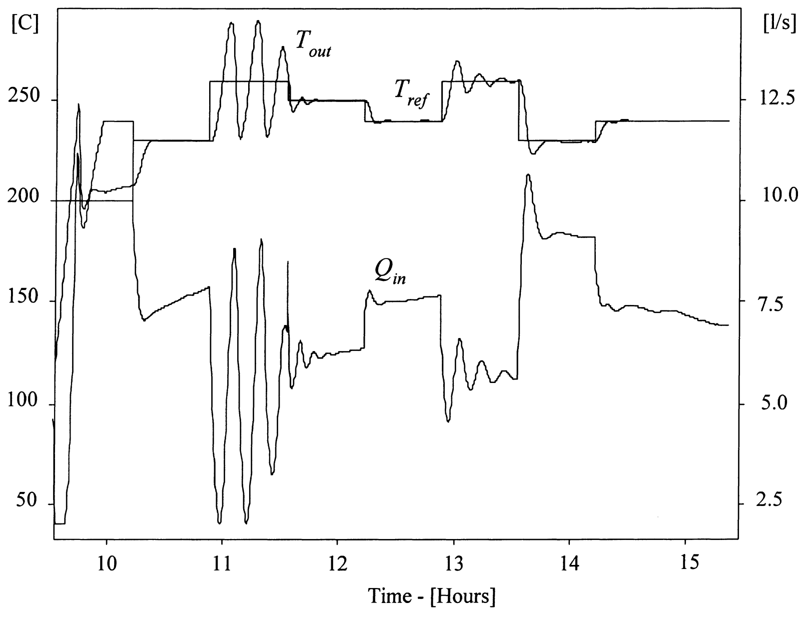

Fig. 10. Simulation 1 – results using a fixed PID controller (C5).

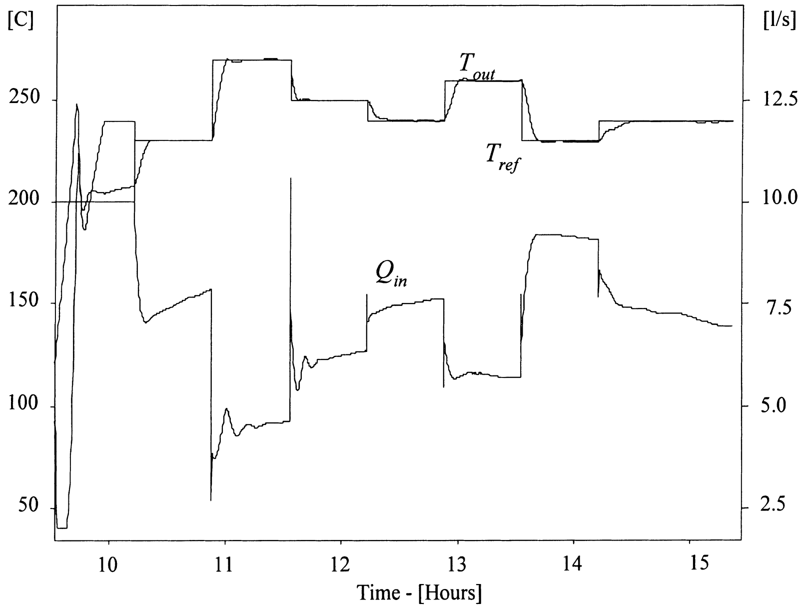

Fig. 11. Simulation 2 – results using the proposed switching strategy.

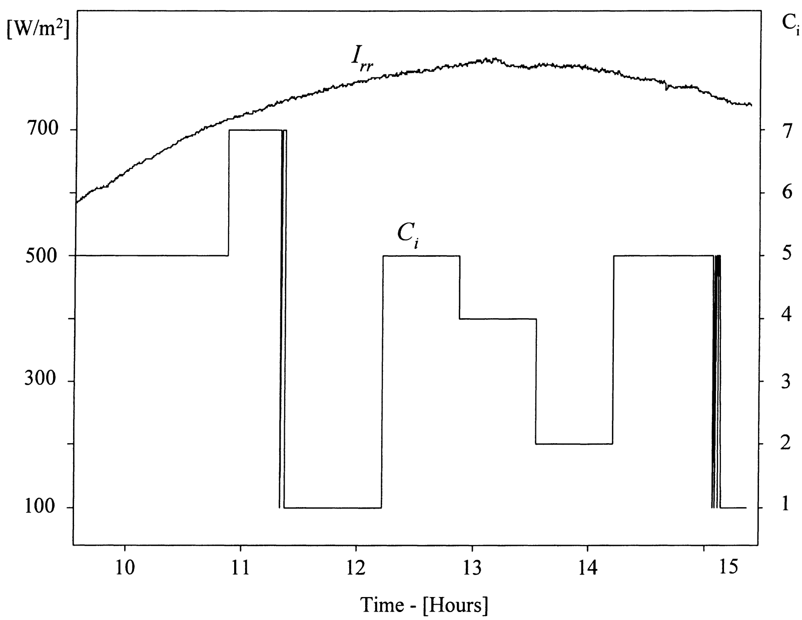

Fig. 12. Simulation 2 – solar radiation and selected controller – 6 July 1998.

3.2. Experiments

The first experiment was carried out on 6 July 1998. The proposed control strategy was tested to cope with the changes in plant dynamics. Fig. 13 shows the results in which several reference temperatures changes have been performed. Also, in order to show the rejection capabilities of the proposed controller, a change in the inlet oil temperature have been done at instant 13 h 25 min.

As can be 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 min. The disturbance rejection capabilities of the controller were also acceptable.

From the use of a PID controller, it should be expected a zero steady state error. The actual error, for instance at instant 12 h 10 min, is justified by the evolution of solar radiation in its daily cycle, which acts as a load disturbance (approximately a ramp) in the output temperature and is not adequately compensated by the integral action of the PID. This experiment has shown that the fuzzy supervisor mechanism, which makes the switch between the PID controllers (shown in Fig. 14), provides a good control strategy.

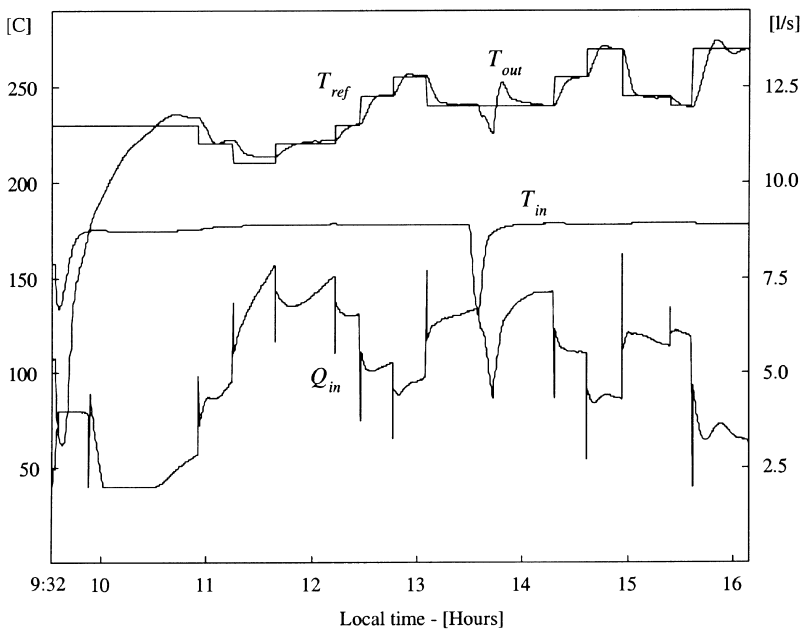

Fig. 13. Experiment 1 – results obtained on 6 July 1998.

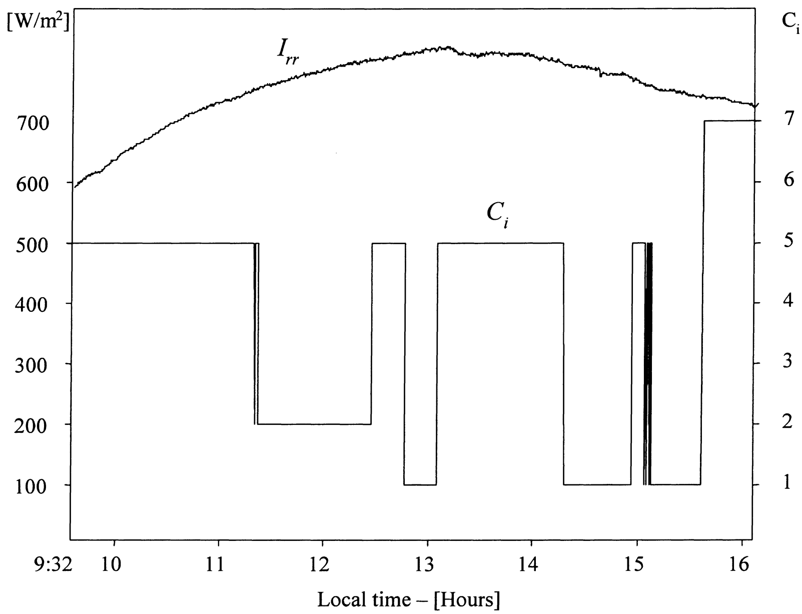

Fig. 14. Experiment 1 – solar radiation and selected controller – 6 July 1998.

The experiment 2 has been carried out on 7 July 1998 and the results can be seen in Figs. 15 and 16. The set point temperature was changed and at instant 14 h 55 min one loop has been suppressed from the field and connected again at instant 15 h 12 min.

After an initial phase the outlet oil temperature reaches the reference. The results are very acceptable in face of the different operating points and the addition/suppression of a collector loop.

Concerning the fuzzy switching supervisor and observing the results, it can be concluded that the adequate controller has been selected to each operating point.

4. Conclusions

A PID based hierarchical control combining a switching supervisor strategy and the c-Means clustering technique has been presented and applied to a distributed collector field of a solar power plant. The process is characterised by different operating conditions, depending on the changes in dynamics caused by variation of the solar radiation, reference temperature, and plant characteristics. Based on a neural network approach off-line trained with experimental data, a set of nominal PID controllers tuned for different operating

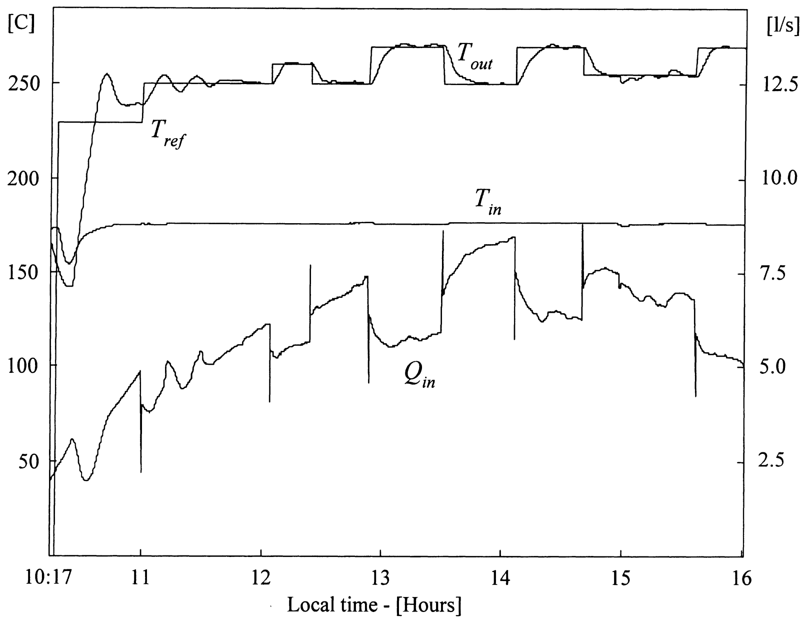

Fig. 15. Experiment 2 – results obtained on 7 July 1998.

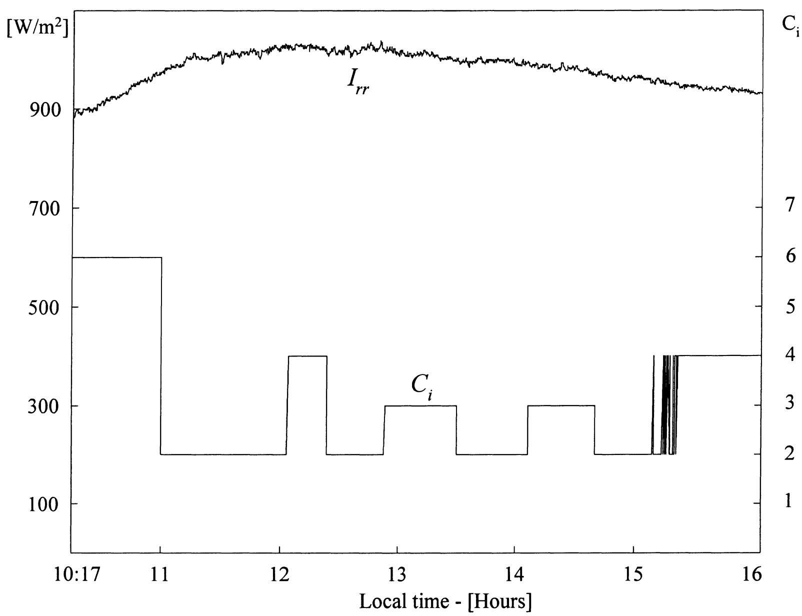

Fig. 16. Experiment 2 – solar radiation and selected controller – 7 July 1998.

points have been designed. Next, the number of nominal PID controllers have been reduced employing a c-Means clustering technique.

Simulation results have shown the effectiveness of the proposed switching strategy. Testes carried out in the solar field at PSA confirm the simulation results and show that the system has robustness with respect to changes in solar radiation, inlet oil temperature and operating conditions.

References

[1] R. Babuska, P. Horacek, Laboratory evaluation of fuzzy controllers. Pre-prints of the IFAC/IFIP/IMACS International Symposium of Artificial Intelligence in Real Time Control, Delft, 1992, pp. 263–268.

[2] M. Berenguel, E. Camacho, F. Rubio, Simulation software package or the acurex field, Internal Report, ESI de Sevilla, http://www.esi.us.es/~beren/libro.html, 1993.

[3] M. Berenguel, E. Camacho, F. Rubio, P. Luk, Incremental fuzzy pi control of a solar power plant, IEE Proc. Control Theory and Applications 144 (6) (1997) 596–604.

[4] J. Bezedek, Pattern recognition with fuzzy objective functions algorithms, Plenum, New York, 1981.

[5] E. Camacho, M. Berenguel, F. Rubio, Application of a gain scheduling generalised predictive controller to a solar power plant, Control Engineer Practice 2 (2) (1994) 227–238.

[6] E. Camacho, F. Rubio, J. Gutierrez, Modelling and simulation of a solar power plant with distributed collector system, IFAC Symposium Power Systems, Modelling and Control Applications, Brussels, 1988.

[7] E. Camacho, F. Rubio, F. Hughes, Self-tuning control of a solar power plant with a distributed collector field, IEEE Control Systems Magazine 12 (2) (1992) 72–78.

[8] F. Coito, J. Lemos, R. Silva, E. Mosca, Adaptive control of a solar energy plant: Exploiting accessible disturbances, Int. Journal of Adaptive Control and Signal Processing 11 (4) (1997) 327–342.

[9] I. French, C. Cox, M. Willis, G. Montague, Intelligent tuning of PI controllers for bioprocess application, Pre-prints of the IFAC/IFIP/IMACS Internat. Symposium on Artificial Intelligence in Real-Time Control, Delft, Netherlands, 1992, pp. 697–702.

[10] J. Henriques, A. Dourado, A multivariable adaptive control using a recurrent neural network, EANN98–Engineering Applications of Neural Networks, Gibraltar, 9–12 June 1998, pp. 118–121.

[11] L. Jin, N. Nikiforuk, M. Gupta, Approximation of discrete time state space trajectories using dynamic recurrent networks, IEEE Trans. Automatic Control 40 (7) (1995) 1266–1270.

[12] R. Ketata, D. Geest, D. Titli, Fuzzy controller: Design, evaluation, parallel and hierarchical combination with a PID controller, Fuzzy Sets and Systems 71 (1995) 113–229.

[13] C. Lee, Fuzzy logic in control systems: Fuzzy logic controller – parts 1 and 2, IEEE Trans. Systems Man Cybernetics 20 (1990) 404–435.

[14] J. Lopez, Acurex filed d.a.s. and control system, Internal Report 08/96, Plataforma Solar de Almeria, 1996.

[15] E. Mamdani, Application of fuzzy algorithms for control of a simple dynamic plant, IEE Proc. D 121 (1974) 1585–1588.

[16] P. Oliveira, P. Lima, J. Sentieiro, Fuzzy supervision on intelligent control systems, European Control Conference ECC91, Grenoble, France, 1991, pp. 1226–1231.

[17] D. Pham, L. Xing, Dynamic system identification using Elman and Jordan networks, in: A. Bulsari (Ed.), Neural Networks for Chemical Engineers, Ch. 23, 1995, pp. 572–591.

[18] R. Pickhardt, R. Silva, Application of a non-linear predictive controller to a solar power plant, Proceedings of the IEEE Conference on Control Applications, Trieste, 1998.
[19] R. Pickhardt, H. Unbehauen, An indirect adaptive predictive controller for linear and non-linear plants, Proceedings of the American Control Conference, 1994, pp. 2585–2589.
[20] L. Rato, D. Borrelli, E. Mosca, J. Lemos, P. Balsa, Musmar based switching control of a solar collector field, European Control Conference ECC97, Brussels, 1–4 July, ConferID 266, 1997.
[21] F. Rubio, M. Berenguel, E. Camacho, Fuzzy logic control of a solar power plant, IEEE Trans. on Fuzzy Systems 3 (4) (1995) 459–468.
[22] P. Werbos, Backpropagation trough time: What it does and how do it, Proc. IEEE 78 (1990) 1550–1560.
[23] L. Zadeh, Fuzzy Sets, Inform. Control 8 (1965) 338–353.