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Supervisory Fuzzy Predictive Control for a Concentrated Solar Power Plant

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Abstract: This paper deals with the design and evaluation of the performance of fuzzy predictive controller in supervisory mode for a solar-concentration-based power plant, with cylindrical-parabolic solar collectors. For the design of the controller, the inner control loops present in this solar platform are included in the model of the plant. That is, a control loop consisting of a PI plus a feed-forward controller is considered for modeling the closed-loop behavior of the plant. With this purpose, an ARIX and a Takagi-Sugeno model are compared. As expected, the Takagi-Sugeno model performs better than the ARIX model. Therefore, Takagi-Sugeno model is used for designing the supervisory control strategy. The proposed control scheme is tested in the ACUREX simulator (the simulator of the Almeria Solar Platform). The tests included in this paper are: set-point changes, variations in the solar radiation, and modifications in the parameters of the inner control loop.

Keywords: Concentrated Solar Power Plant, Distributed Solar Collector, Predictive control, Supervisory control, Takagi and Sugeno fuzzy model

1. INTRODUCTION

Currently, there is a huge international interest in the development of renewable-sources-based energy generation technologies. In this field, solar-based generation has emerged as the main alternative for energy production. Particularly, the solar concentrator technology has reached sufficient maturity to be included in the generation market. Indeed, within the next few years is expected that this technology will be present in the Chilean energy matrix, although such technology is already included in the power system of several European countries. The maturity level achieved by the solar concentration technology obeys to its power generation capabilities. In fact, the use of cylindrical-parabolic solar concentrators allowed having the largest power plants based in alternative energy. Arguing the importance of energy in the human-beings live, this work focuses on the design of a supervisory predicitve control strategy for a cylindrical-parabolic power plant. Such power plants consist of a reflecting surface curved in a parabolic shape, so the beams are concentrated at the focus, through which passes a receptor pipe. Inside the pipe there is thermal oil in charge of storing the solar energy and transmitting it to a steam generator to spin a turbine. Aiming this, the oil is forced to flow along the pipe by using a small pump (Haas et al. (2012)). Notice that in solar-concentration-based power energy plants the energy source is the sunlight. Hence, determining the amount of available energy is a hard task. Mainly because the sunlight depends upon the weather conditions, the latitude, and the geographical factors (Richter et al. (2009)). Other factor determining the energy production of solar-concentration-based power plants is the temperature of thermal oil at the end of the pipe. This temperature determines the usefulness of the solar resource in the energy production. Therefore, a control strategy is required in order to maximize the use of the available sunlight for power generation. Such control strategy must be robust enough for regulating the temperature of the oil at the end of the pipe despite of solar radiation variations, changes in the mirror reflectivity and/or in the inlet temperature of the oil. The achievement of the control objective should be done by manipulating the flow of the thermal oil along the pipe.

With the purpose of controlling the temperature of the thermal fluid at the end of the pipe, several control strategies have been reported in the literature. For example, in Barao (2000) and Barao et al. (2002) a fuzzy control strategy including Lyapunov based adaptation for solar-collector power plants was proposed. In Gil et al. (2002a, 2002b) a nonlinear adaptive constrained model predictive control (MPC) scheme was proposed. In this strategy an artificial neural network was used as a prediction model, because of its intrinsic nonlinear modeling capabilities. Here steady state compensation was added in order to improve the closed-loop system behavior. In Silva et al. (2002, 2003a, 2003b), a control scheme based on fuzzy logic models was proposed. In this approach, the partial differential equations modeling the behavior of the temperature of the thermal fluid along the pipe were approximated by fuzzy models. With these models, the proposed control strategy was developed. In the same line, Cirre et al. (2005a) proposed fuzzy model based control strategies for controlling thermal oil at the end of the pipe in a solar-collector-based power plant. In Cirre et al. (2005a) lumped-parameter models were used in the control strategy design. The resulting controller has shown excellent results when tested at the real plant and is very adequate for the starting up phase of the operation. In Flores et al. (2005) an MPC based on fuzzy optimization was developed, accounting the uncertainty of the components in the typical MPC objective function. Although the approaches previously discussed seem to have the expected performance, they were not enough for achieving the control objective in a solar-collector-based power plant. This motivates some more recent analysis as the presented in Cirre et al. (2007). Here, the authors discussed the effect of the varying delays between the inlet and outlet temperatures of the thermal oil. As a consequence, a performance improvement of the model-based controller during the startup and in presence of disturbances in the inlet oil temperature was accomplished. In Camacho et al. (2007) the performance of different MPC strategies such as adaptive MPC, robust MPC, and non-linear MPC with neural networks was analyzed. Finally, based on the results of the works done by Cirre et al. (2007) and Camacho et al. (2007), in Galvez-Carrillo et al. (2009) a non-linear MPC was proposed for dealing with the varying delays. Here the authors also included a dead time compensator, which used the nonlinear extended prediction self-adaptive algorithm. Finally, alternative control strategies for the solar-collector-based power plants are proposed in Cirre et al. (2003), in Pérez de la Parte et al. (2008), and in (Cirre et al. 2004, 2005b; 2009; Berenguel et al. 2005). In Cirre et al. (2003) a robust control scheme was proposed. Such scheme was developed considering quantitative feedback theory as a mathematical framework. In Pérez de la Parte et al. (2008) three sliding-mode based predictive controllers were developed and compared, namely, a reaching law, an equivalent control and a nonlinear general predictive controller. All of them had as a reference value, the desired temperature surface along the pipe. And in (Cirre et al. 2004, 2005b; 2009; Berenguel et al. 2005) hierarchical multilayer control schemes were proposed. In these hierarchical control schemes the upper layer automatically determines the optimal operating points of the power plant, according to an economical cost function. Such points were transmitted to the lower layer where a reference tracking control was performed.

Since there exist several places with privileged solar radiation conditions (e.g. the northern of Chile), since the growing energy demand cannot be stopped in the near future, and since solar-collector-based power plants arise as an environmentally friendly solution for energy production, and since there are incentives from the governments and the private sector for interesting in this technology, the development of control strategies allowing enhance the performance of such power plants take on new importance. In this way, in the current paper an MPC based supervisory control is proposed. In the proposed scheme, the direct control actions are determined by a previously designed configuration based on a PI plus a feed-forward controller, while the MPC provides the optimal reference value for such inner control loop. The idea behind this controller is that the inner loop provides a faster response in presence of disturbances while the MPC drives the whole system to the desired values in an optimal way. The combination of the control efforts of both the inner and outer loops allow maximizing the use of the available solar resource for energy production, even in the cases where clouds reduces the sunlight in some sections of the collector field. The simulator of the Almería Solar Platform was used for evaluating the performance of the proposed scheme. Aiming this, sunlight variations associated with the presence of clouds, and the bad-tuning of the PI controller were used to show the capabilities of the supervisory controller. The remaining of this paper is organized as follows: In Section 2 the description of the solar power plant is presented. Section 3 gathers with the description of the fuzzy models used for predicting the power plant behavior in the MPC. The design of the supervisory control is introduced in Section 4. Finally, in Sections 5 and 6 the simulation results and concluding remarks are presented, respectively.

2. DESCRIPTION OF SOLAR POWER PLANT

The system considered for the design of the supervisory fuzzy MPC is the Almería Solar Platform. This solar power plant consists of a solar collector field whose collectors are arranged in 20 rows, with 10 parallel loops. Each loop belongs to the cylindrical-parabolic type, and is equipped with the Acurex type elevation tracking system. In total, the collector field has 480 modules oriented east to west forming an effective mirror area of 2,476 m^2. The thermal oil used in this plant is Santotherm 55, which is a synthetic oil allowing to reach temperatures up to 300 °C. Since the density of the thermal oil used in Almería is highly dependent on the temperature, a sole storage tank is used, and the principle of the thermoclines is used for storing up to 2.3 MWt. Fig. 1 shows and schematic diagram of the Almeria solar plant. For such solar plant, a model using partial differential equations was derived in (Carmona (1985)). This model is used in the current paper for evaluating the performance of the proposed control strategy. For this purpose, the parameters as well as the simulation procedure proposed in (Camacho et al. (1997)) for the Almeria power plant was considered.

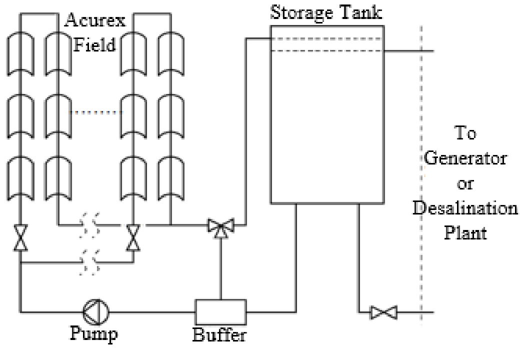

Fig. 1. Schematic diagram of the collector field.

In addition to the system dynamics, an inner control loop is considered. Such control loop consists of a PI plus a feed-forward controller as shown in Fig. 2. In Fig. 2 $T_r(k)$ is the set point, $T_{ff}(k)$ is the control variable for the feedforward controller, $V_s(k)$ is the oil flow that the feed-forward controller demands from the pump, $T_{out}(k)$ is the outlet oil, $e(k)$ the tracking error, $T_{amb}(k)$ is a disturbance corresponding to the measured outside temperature, $I_{rr}(k)$ the solar radiation measured in the plant, and $T_{in}(k)$ is the inlet oil temperature.

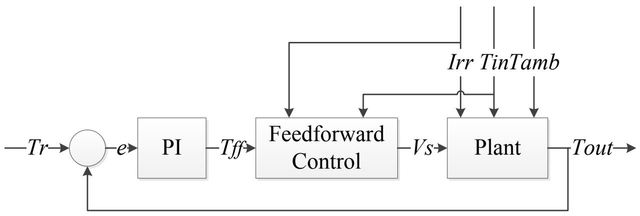

Fig. 2. Control loop for the solar power plant.

The control scheme shown in Fig. 2 is in charge of regulating the temperature of the oil at the end of the pipe to the desired value. The feed-forward control is added for compensating the changes in the irradiance, in the temperature outside the power plant, and in the inlet temperature of the oil. The PI controller is added to eliminate the steady-state error of the output. Also, from (Camacho et al. (1997)) the value of $V_s(k)$ can be obtained from $I_{rr}(k)$ and $T_{in}(k)$ according to (1).

$$V_s(k) = \frac{0.7869 I_{rr}(k) - 0.485\left(T_{ff}(k) - 151.5\right) - 80.7}{T_{ff}(k) - T_{in}(k)} \tag{1}$$

3. FUZZY MODELING OF THE SOLAR POWER PLANT

3.1 Fuzzy identification

The prediction model considered in this paper is a Takagi-Sugeno (TS) fuzzy model, where $u(k) = T_r(k)$ and $y(k) = T_{out}(k)$. The procedure for identifying the structure and parameters of the fuzzy model is shown in Fig. 3 (Sáez & Cipriano, 2001). In such procedure, the first step is to make a data selection for training, testing, and validation, the second step is to select the relevant variables, the third step is to optimize the structure by e.g. sensitivity analysis, the fourth step is to perform a parameter identification procedure, and the fifth step is to validate the resulting model. In the Almeria solar plant, data corresponding to 35 days of operation was simulated. Then, the data was divided as follows: 21 days long for training, 7 days long for testing, and 7 days long for validating the model. Also, for each rule an ARIX model was considered with $na = nb = 10$ and $nk = 0$. Then, the fuzzy model is given by

$$y(k) = f_{TS}\left(y(k-1),\ldots,y(k-10),\Delta u(k-1),\ldots,\Delta u(k-10)\right) \tag{2}$$

Using the Root Mean Square (RMS) error with respect to the data sets for training and testing the number of rules and regressors was determined, varying the number of clusters from 1 to 6, obtaining the model with two rules (3) for the Almería solar plant. In Eq. (3) A_r^i is the i-th fuzzy set and y^r is the output of the rule r. The output of the model is given by (4), where w_r is the degree of activation of the rule r, with $w_r(k) = \prod_{i=1}^{na+nb} \mu_i^r(k)$, where $\mu_i^r(k)$ is the degree of membership of the fuzzy set S_i^r. In this procedure both the parameters of the premises and consequences were identified. The parameters of the premises were computed using fuzzy c-means and the parameters of the consequences were computed using the TS method based on least squares (Takagi & Sugeno, 1985).

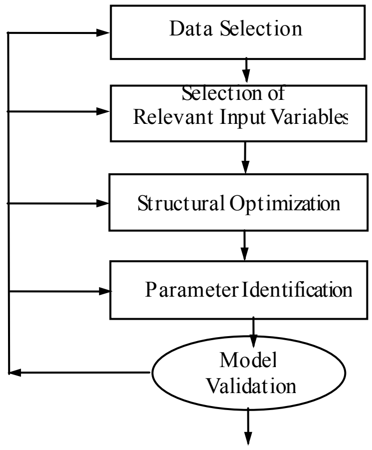

Fig. 3. Procedure for fuzzy model identification.

$$\begin{aligned}
&\text{If } y(k-1) \text{ is } A_1^1 \text{ and } y(k-4) \text{ is } A_2^1 \text{ and } y(k-5) \text{ is } A_3^1 \\
&\text{and } y(k-6) \text{ is } A_4^1 \text{ and } y(k-7) \text{ is } A_5^1 \text{ and } y(k-8) \text{ is } A_6^1 \\
&\text{and } \Delta u(k-1) \text{ is } A_7^1 \text{ and } \Delta u(k-4) \text{ is } A_8^1 \text{ and } \Delta u(k-8) \text{ is } A_9^1 \\
&\text{then } y^1(k) = 0.7008\, y(k-1) - 0.0229\, y(k-4) \\
&-0.0208\, y(k-5) - 0.0109\, y(k-6) - 0.0446\, y(k-7) \\
&-0.0062\, y(k-8) + 0.0964\Delta u(k-1) + 0.0229\Delta u(k-4) \\
&+0.0062\Delta u(k-8) + 0.0195 \\
\\
&\text{If } y(k-1) \text{ is } A_1^2 \text{ and } y(k-4) \text{ is } A_2^2 \text{ and } y(k-5) \text{ is } A_3^2 \\
&\text{and } y(k-6) \text{ is } A_4^2 \text{ and } y(k-7) \text{ is } A_5^2 \text{ and } y(k-8) \text{ is } A_6^2 \\
&\text{and } \Delta u(k-1) \text{ is } A_7^2 \text{ and } \Delta u(k-4) \text{ is } A_8^2 \text{ and } \Delta u(k-8) \text{ is } A_9^2 \\
&\text{then } y^2(k) = 0.6427\, y(k-1) - 0.0258\, y(k-4) \\
&-0.0080\, y(k-5) - 0.0129\, y(k-6) - 0.0522\, y(k-7) \\
&-0.0083\, y(k-8) + 0.1403\Delta u(k-1) + 0.0258\Delta u(k-4) \\
&+0.0083\Delta u(k-8) + 0.0187
\end{aligned} \tag{3}$$

$$y(k) = \frac{\sum_{r=1}^{2} w^r(k)\, y^r(k)}{\sum_{r=1}^{2} w^r(k)} \tag{4}$$

3.2 TS fuzzy model performance

In order to determine the capabilities of the TS fuzzy model for the Almería solar power plant, a comparison with an ARIX model of the same power plant was done. ARIX model was used as the base-line for the comparison because often ARIX models are used as prediction model in MPC schemes. For identifying the parameters of the ARIX model, the same data set used for identifying the TS fuzzy model were used. The identified ARIX model is the following:

$$\begin{aligned} y(k) &= -0.8874\,y(k-1) - 0.0999\,y(k-2) \\ &\quad +0.1838\Delta u(k-1) + 0.001 + w(k)/\Delta \end{aligned} \tag{5}$$

Table 1 summarizes the RMS of both the ARIX and the TS fuzzy models for both predictions one and fifteen time steps ahead. In such Table is evident that in the fifteen steps in-advance prediction case the TS fuzzy model has a better performance than the ARIX model in the validation data set. This corroborates the expected generalization capabilities of the TS fuzzy model. Fig. 4 shows the 15 steps prediction with the ARIX and TS fuzzy models. Notice that the prediction done with the TS fuzzy model converges to the real value faster than the one done by the ARIX model. This bears out the results presented in Table 1.

Table 1. RMS indexes for the model comparison.

	RMSE One-step-ahead		RMSE 15- steps-ahead	
Data set	ARIX [°C]	TS [°C]	ARIX [°C]	TS [°C]
Training	1.309	1.339	9.120	6.447
Test	1.438	1.454	9.884	6.890
Validation	1.146	1.141	8.295	5.723

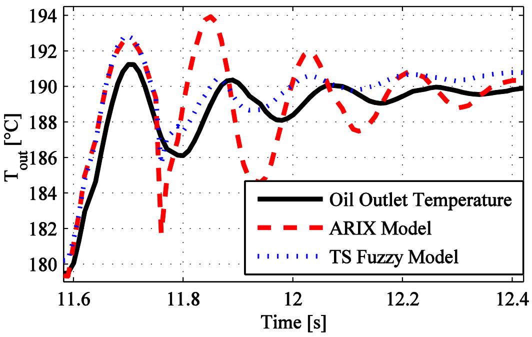

Fig. 4. 15 steps prediction for $T_{out}(k)$.

4. SUPERVISORY FUZZY PREDICTIVE CONTROL

In this Section the proposed MPC controller is described. Fig. 5 shows the block diagram of the supervisory control. In this scheme, an MPC is added in order to maximize the use of the available solar thermal energy for energy production. The notation in Fig. 5 corresponds to the notation introduced in Section 3, with r the reference for the supervisory control.

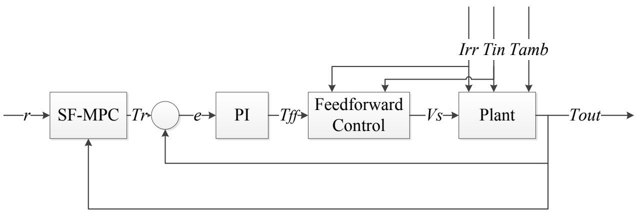

Fig. 5: Supervisory MPC control loop.

Let $\hat{y}(k+i|k)$, $r(k+i)$, and $\Delta u(k+i)$ denote the predicted output, the reference value, and the change of the control actions at time step k, with $k+i|k$ denoting the variable at time step $k+i$ given the conditions at time step k. Let δ_i, λ_i, N_1, N_2, and N_u be the relative weight for tracking error, the relative weight for the changes in the control actions, the minimum and maximum prediction horizons, and the control horizon respectively. Then, the reference tracking cost function is used for designing the MPC controller is given by (6).

$$\begin{aligned} J(k) &= \sum_{i=N_1}^{N_2} \delta_i \left[r(k+i) - \hat{y}(k+i|k) \right]^2 \\ &\quad + \sum_{i=1}^{N_u} \lambda_i \left[\Delta u(k+i-1) \right]^2 \end{aligned} \tag{6}$$

In this work $\delta_i = 1$, $N_1 = 1$, $N_2 = 15$, and $N_u = 15$. The value of λ_i was obtained using (7) as performance index, with k_T the total simulation time, and $\lambda_i = \lambda$ for $i = 1, \cdots, N_u$. It is worth to point out that the value of λ_i may render the closed-loop system unstable. Indeed, in the case of the solar plant $\lambda < 0.4$ make the system becomes unstable, and $\lambda = 0.8$ minimizes the value of η in (7). Hence, that value was used in the proposed MPC controller.

$$\eta = \left(\frac{1}{k_T} \right)^2 \left(\left(\sum_{k=1}^{k_T} \sqrt{\left(y(k) - r(k) \right)^2} \right)^2 + \lambda \left(\sum_{k=1}^{k_T} \sqrt{\Delta u(k)^2} \right)^2 \right) \tag{7}$$

With the selected values of the parameters the proposed MPC was implemented following the generalized predictive control (GPC) procedure (Clarke et al. (1987)), and assuming one GPC per rule. Thus, the control actions of the supervisory fuzzy MPC (SF-MPC) are given by (8), where the premises are the same as in (3).

$$\Delta u = \frac{\sum_{r=1}^{N_r} w^r(k) \Delta u^r(k)}{\sum_{r=1}^{N_r} w^r(k)} \tag{8}$$

5. RESULTS

The performance of the SF-MPC was compared with the control configuration in Fig. 2 considering normal operation, changes in the radiation, and in a PI bad tuning scenario. The inlet oil temperature, the environmental temperature, and the sunlight used in the simulations are shown in Fig 6. As comparison indexes, the maximum overshoot M_p, the rising time t_e, the stabilization time t_s, and the tracking error η_y were considered. Fig.7 shows the behavior of $T_{out}(k)$ and $V_s(k)$ when a step-up in the set-point of the outlet oil temperature is applied to the system. Comparison results are presented in Table 2. In this Table, the solar power plant presents a greater rise time when the MPC is added. However, there is no overshoot and the RMS value of the tracking error is considerably reduced. Also, the stabilization time is comparable with both controllers. Since the overshoot is avoided and the reference tracking error is reduced it is possible to conclude that the SF-MPC performs better than the original configuration. Moreover, overshoot avoidance will allows increasing the operational range of the power plant, because of the oil can reach temperatures closest to its critical value. Notice that the manipulated variable does not reach a constant value, because of the radiation profile. Since radiation decreases in the afternoon the flow of oil should be decreased for maintaining its temperature at the desired value.

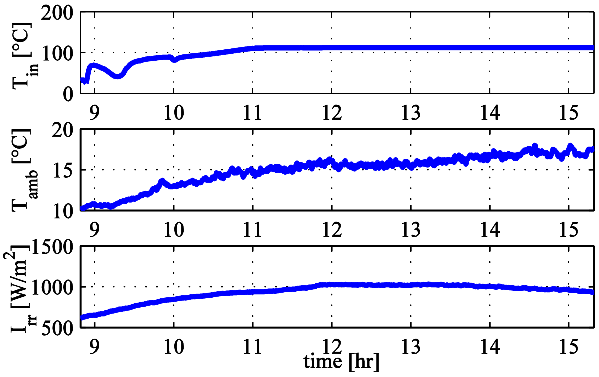

Fig. 6: (Top) Inlet oil temperature, (Middle) Environmental temperature (Bottom), Solar radiation.

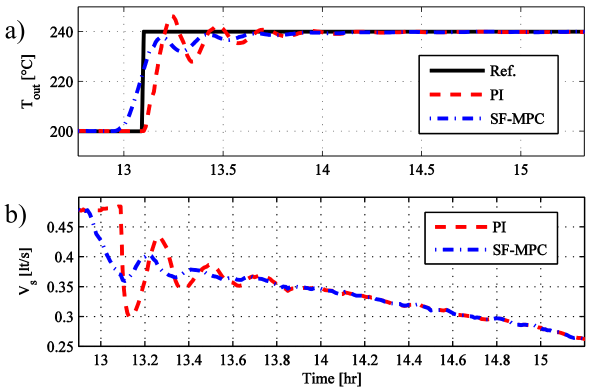

Fig. 7: Behavior of the plant with a step-up in the desired outlet temperature (a), and of the manipulated variable (b).

After testing the performance of the power plant with the SF-MPC, the performance of that scheme was tested in presence of high radiation changes, viz., a loss of 25% of the radiation was considered. Fig. 9 presents the simulation results obtained for both original and SF-MPC. Table 3 summarizes the results obtained in this test. From such Table it is possible to conclude that the SF-MPC does not enhance the system performance with respect to dramatic changes in the sunlight.

Table 2. Evaluation of the Controllers.

	Step-up		Step-down	
	PI	SF-MPC	PI	SF-MPC
M_p[%]	2.64	0.00	4.23	0.00
t_e[min]	4.55	9.10	2.60	8.45
t_s[min]	91.65	55.25	51.35	57.85
η_y[°C]	5.67	3.68	5.38	3.75

Finally, a scenario with an unexpected behavior of the inner control loop is considered, namely, a change in the tuning of the PI controller. Fig. 10 shows the results obtained, where is evident that adding the SF-MPC improves significantly the performance of the power plant. In fact, despite of the reference changes the supervisory controller drives the system to the reference value. This is directly reflected in the tracking error (see Table 3).

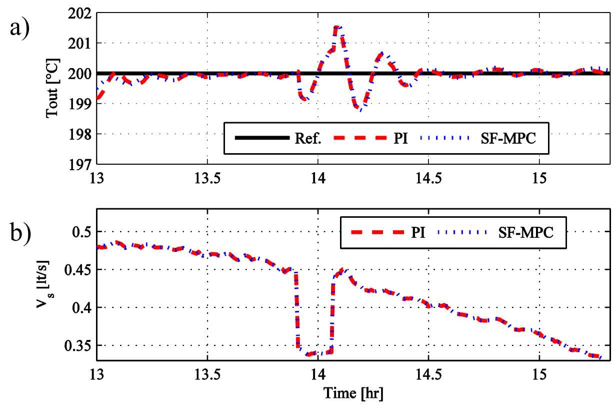

Fig. 9: Behavior of the plant facing a passing cloud (a) Controlled variable, (b) Manipulated variable.

Table 3. Tracking error.

	PI [%]	SF-MPC [%]
Passing Cloud	0.1792	0.1929
Detuned PI	5.1859	4.6663

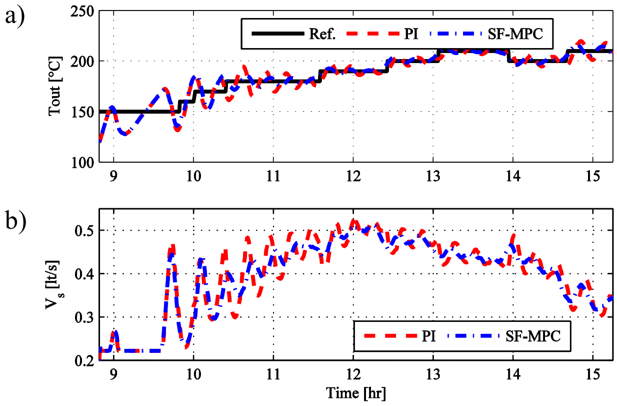

Fig. 10: Behavior of the plant with detuned PI, and of the manipulated variable.

6. CONCLUSIONS

In this paper the design of a supervisory predictive control scheme for the Almeria solar power plant based on a TS fuzzy model was presented. Since this solar plant is operative supervisory strategy was selected as an alternative for improving its performance without changing the control loops currently installed in the plant. From the development of the simulated experiments, it is possible to conclude that the supervisory control enhance the performance of the plant. Such improvement lies in the achievement of higher temperatures in the outlet oil, and in the expected increasing in the power produced associated with the higher outlet oil temperature. From the control theory point of view, adding the supervisory control loop also provided some improvements in the closed-loop behavior. For instance, the overshot exhibited by the plant in presence of set-point changes was eliminated without changing the control loops currently installed in the plant. Moreover, the stabilization time was reduced as well as the tracking error. It is worth to point out that often improving the system performance implies a reduction of its robustness. However, in this case only large changes in solar radiation significantly affected the performance of the solar power plant with supervisory control. Indeed, it was demonstrated that the supervisory control is able to drive the system to the desired operating points even though the controllers in the inner loop were not well tuned. Given the simulation results obtained in this paper, the next step is to implement the proposed strategy explicitly including the uncertainty in solar radiation, environmental temperature, and variations in the inlet temperature due to changes in the power.

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