Fuzzy Predictive Control of a Solar Power Plant

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***Abstract*—This paper presents the application of fuzzy predictive control to a solar power plant. The proposed predictive controller uses fuzzy characterization of goals and constraints, based on the fuzzy optimization framework for multi-objective satisfaction problems. This approach enhances model based predictive control (MBPC) allowing the specification of more complex requirements. A brief description of the solar power plant and its simulator is given. Basic concepts of predictive control and fuzzy predictive control are introduced. Two fuzzy predictive controllers using different membership functions are designed for a solar power plant, and they are compared with a classical predictive controller. The simulation results show that the fuzzy MBPC formulation, based on a well proven successful algorithm, gives a greater flexibility to characterize the goals and constraints than classical control.**

***Index Terms*—Fuzzy constraints, fuzzy goals, fuzzy optimization, predictive control, solar power plant.**

I. Introduction

ONE OF THE main characteristics of a solar power plant is that the primary energy source (solar radiation) cannot be manipulated. Besides, the solar radiation intensity depends on daily and seasonal cycle variations, like clouds, atmospheric humidity, and air transparency. This justifies the relevance of solar power plant control.

This study considers the Acurex distributed collector solar field, located at the Almería Solar Platform, Almería, Spain. In this solar power plant, the main control goal is to maintain constant outlet oil temperature, despite the operation conditions changes, by manipulating the field oil flow. To maintain constant outlet temperatures during the day while the solar conditions changes, significant flow variations are required. This produces considerable variations in the dynamics of the process. Hence, conventional control algorithms based on a simplified model of the process, for example the linear quadratic Gaussian (LQG) regulator, proves to be ineffective [1]. However LQG/linear transfer recovery (LTR) regulator gives better results even when the working conditions are far from the ones that LQG controller has been designed for [2].

Due to its nonlinear characteristics, the Acurex solar collector field has been used as an experimental platform for the application of many modern control algorithms [3].

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In 1992, Camacho *et al.* [4] described a self-tuning proportional–integral (PI) controller for this solar plant, based on a pole assignment approach. In order to compensate the measured disturbances, a feedforward controller is included. The self-tuning controller is capable to deal with changes in the operating conditions of the plant.

Later, several model based predictive control algorithms have been implemented and experimentally tested. For example, Camacho *et al.* [5] presented an adaptive generalized predictive controller (GPC). The algorithm is based on reaction curve modeling that uses recursive least squares estimation. The proposed controller is successfully compared with a self-tuning PI controller [4].

Camacho *et al.* [6] proposed a gain scheduling GPC, based on the fact that the controller's parameters depend on the same variables that define the operating condition. In this case, the dynamics of the field are mainly conditioned to the oil flow, which can be used to change the controller's parameters. The main advantage of this controller compared to the previous adaptive algorithms is that the controller parameters are fixed.

Camacho and Berenguel [7] described a GPC algorithm based on a nonlinear model. In this case, the nonlinear model is used to generate an estimation of the *free response* of the process, due to past control actions and disturbances. This term is combined with the *forced response*, which is calculated using a linear model. The nonlinear model allows the controller to deal with changes in the dynamics of the process. Camacho *et al.* [8] described an extension of the mentioned algorithm, in which the free response is based on a neural network obtaining a control scheme that shows very good performance.

In 1995, Rubio *et al.* [9] presented a fuzzy logic controller for the solar plant. The fuzzy controller is based on rules obtained using expert knowledge of the process. Subsequently, Gordillo *et al.* [10] proposed a genetic design of a fuzzy logic controller. The genetic algorithm is used to optimize the parameters of the fuzzy controller.

Cardoso *et al.* [11] and Henriques *et al.* [12] described a fuzzy switching supervisor PID control strategy for the solar plant. The fuzzy supervisor controller measures actual data available from the plant providing a way to switch between several fixed controllers. Additionally, the local PID controllers are offline tuned, with a dynamic recurrent neural network with pole placement. In 1999, Henriques *et al.* [13] proposed the same idea but the fuzzy switching is made using c-means clustering.

Distinctly, Juuso *et al.* [14] presented a fuzzy PI controller applied to the solar plant. The results show that the fuzzy algorithm is very robust in various difficult operating conditions.

Pickardt [15], [16] described an indirect adaptive controller LQG and GPC for the solar plant. The algorithm uses three or five linear auto regressive with moving average and exogenous inputs (ARMAX) models and contains an online identification procedure to determine and to update the corresponding model

Fig. 1. Panoramic view of the Acurex solar collectors.

of the operating point. In this case, adaptive LQG and GPC are designed and compared, obtaining similar satisfactory results.

Johansen *et al.* [17] proposed a gain-scheduled control for the solar plant. In this case, the algorithm uses high-order local linear auto regressive with exogenous inputs (ARX) models and the local linear controllers are designed based on pole placement. This author's forecoming work describes a distributed model based controller for the solar plant. Stability of the closed-loop is proven using Lyapunov conditions.

In order to compare fuzzy predictive control with classical predictive control, this paper considers a simple MBPC controller based on a linear model of the solar collector field. The system is kept around the operation point and no "hard" constraints are imposed to the process. A fuzzy predictive controller is designed using the same linear model, but applying fuzzy characterization to goals for the controlled variable error and constraints over the manipulated variable.

This paper starts with a brief description of the solar power plant, including the process and simulator description. Next, a classical predictive control algorithm for the solar power plant is described. The fuzzy goals and constraints characterization of the predictive algorithm is explained. Finally, the application to the solar power plant simulator is shown.

II. Solar Power Plant

A. Process Description

The considered solar power plant is located in Almería, Spain. The main objective of the solar plant, based on a distributed collector field, is to collect solar energy by heating oil passing through the field (see Fig. 1).

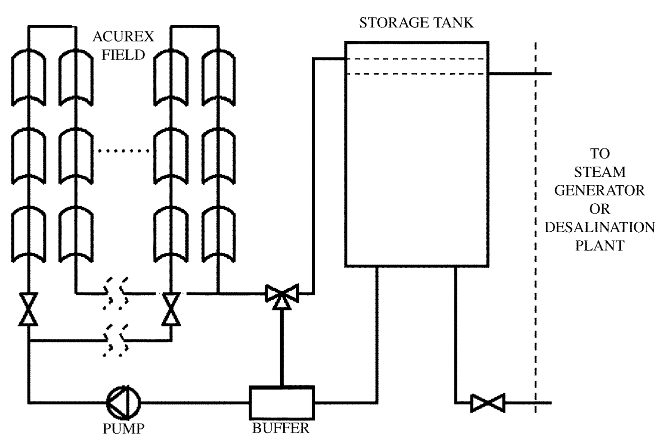

Fig. 2. Schematic diagram of the Acurex distributed collector field.

As shown in Fig. 2, the field consists of 480 collectors. These collectors are arranged in 20 rows that form ten parallel loops and lie along an east–west axis [4].

The field is also provided with a tracking system, which causes the mirrors to revolve around an axis parallel to the pipe, to enable the varying inclination of the sun to be followed. The cold inlet oil is extracted from the bottom of a storage tank and is passed through the field using a pump located in the field inlet. This fluid is heated and then introduced back into the storage tank to be used for electricity generation.

B. Simulator Description

The plant can be described by a set of nonlinear distributed parameter equations obtained from energy and mass balance.

The dynamic of the process is given by the following main partial differential equations [18]:

$$\rho_m c_m A_m \frac{\partial T_m}{\partial t} = I\eta_0 D - h_L G(T_m - T_a) - Lh_T(T_m - T_f) \quad (1)$$

$$\rho_f c_f A_f \frac{\partial T_f}{\partial t} + \rho_f c_f V \frac{\partial T_f}{\partial x} = Lh_T(T_m - T_f) \quad (2)$$

where m and f subscripts are related to the metal and oil fluid (l/s), respectively. Also

- t time (s);
- x position (m);
- ρ oil density $(\mathrm{kg/m^3})$;
- c specific heat of oil (J/kgK);
- A cross-section of the pipeline $(\mathrm{m^2})$;
- T outlet oil temperature $(^\circ\mathrm{C})$;
- I solar radiation (W/m^2);
- η_o optical efficiency;
- D width of the mirror (m);
- h_L overall thermal loss coefficient (W/m^2K);
- G exterior diameter of the pipeline (m);
- T_a environment temperature $(^\circ\mathrm{C})$;
- L inner diameter of the pipeline (m),
- h_T metal-fluid transmission coefficient (W/m^2K),
- V volumetric oil flow rate (m^3/s).

In order to develop the solar power plant simulator, a hundred distributed parameter models representing different sections of the collector field are merged into a model of the plant [3].

III. Classical Predictive Control Algorithms

Model based predictive control (MBPC) involves a complete family of controllers whose basic concepts are (see Fig. 3).

1) Use of an *explicit model* to predict the process outputs at discrete future time instants, over a prediction horizon.
2) Computation of a sequence of *future control actions* through the optimization of a certain objective function, which considers given operation constraints and desired reference trajectories for processes' outputs.
3) *Receding horizon strategy*, i.e., the optimization process is repeated at each sampling instant and the first action in the calculated control sequence is applied [19].

These three characteristics allow MBPC to handle multivariable, nonminimum phase, open loop unstable and nonlinear processes, with a long time delay or including constraints for manipulated and/or controlled variables, if necessary.

At instant t, future process outputs are predicted using an explicit model over the prediction horizon N_p. The predictions depend on known values of the manipulated and controlled variables and the future control actions $u(t+j|t)$ over the control horizon N_u (where the notation $u(t+j|t)$ indicates that the future control signals depend on the conditions at time t). It is assumed that $N_u \leq N_p$ and that $u(t+j|t)$ remains constant for $j = N_u, \ldots, N_p$. The constant N_p is related to the response time of the process and N_u is usually chosen to be equal to the model order.

The control sequence is obtained from the optimization of an objective function, which describes the goals that the control strategy wants to achieve. The optimization process can include "hard" or "soft" constraints if they are considered in the objective function [20]. Classical MBPC uses an objective function that minimizes the control effort Δu and the error between the predicted outputs and the set points w, during the prediction and the control horizon, respectively, as is shown in (3) [19]

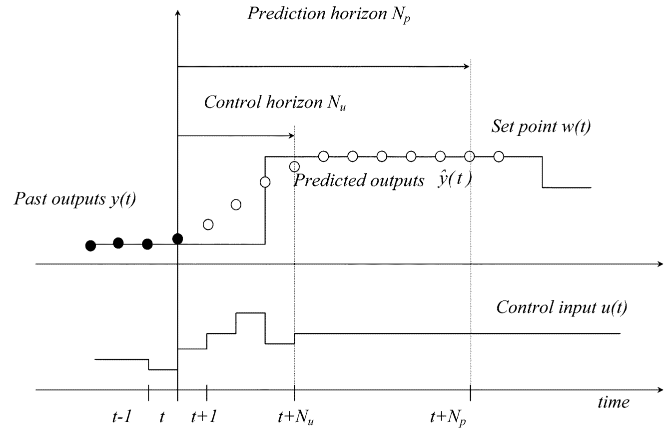

Fig. 3. MBPC strategy.

$$J = \sum_{j=N_1}^{N_p} \delta(j)\left(\hat{y}(t+j|t) - w(t+j)\right)^2 + \sum_{j=1}^{N_u} \lambda(j)\left(\Delta u(t+j-1|t)\right)^2 \quad (3)$$

where $\hat{y}(t+j|t)$ is the expected value of the predicted output at instant $t+j$ with known history up to time t. Parameters $\delta(j)$ and $\lambda(j)$ weight every term involved in the optimization problem. These values can change while the time is evolving to priorize, for example, the final error or the transient period. The value of the parameter N_1 usually is settled as the "dead time" of the control action over the process, but if it is necessary, it can be greater.

For linear unconstrained systems, this tractable convex optimization problem can be solved analytically. However, in general applications it is common to consider constraints or nonlinearities of the process, and in these cases the problem must be solved by using numerical (usually iterative) methods. Further considerations about this subject will be discussed in Section IV.

IV. Fuzzy Goals and Constraints Characterization

Model-based fuzzy predictive control combines the basic idea of traditional predictive control using an objective function which results from the aggregation of different fuzzy criteria based on operator knowledge about the process and its requirements. This principle is represented in Fig. 4 [21].

As in classical MBPC, predictions for future values of process outputs for a given control sequence are obtained through linear or nonlinear models and a receding horizon strategy is applied. Because in reality the cost function is generally only an approximation of the desired control performance, this new methodology suggests the use of fuzzy goals and constraints instead of the typical quadratic criterion.

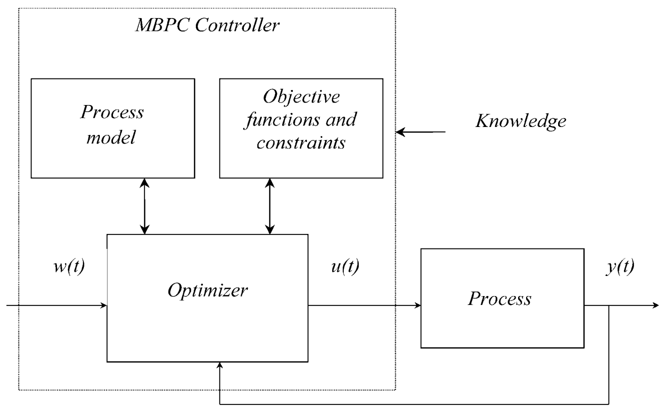

Fig. 4. Classical and fuzzy MBPC basic schemes.

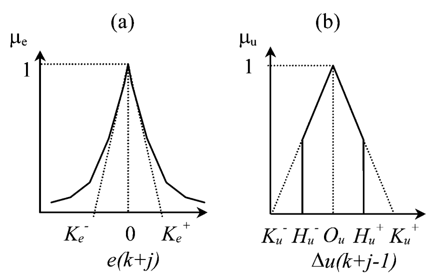

Fig. 5. Membership functions representing satisfaction. (a) Fuzzy goal consisting on minimizing an error. (b) Fuzzy constraint that keeps the change in the control action in a desired range.

There is more flexibility in the definition of the optimization criteria than in the case of traditional predictive control; in fact, both the fuzzy membership function for the goals or constraints and their aggregation operator can be arbitrary selected.

It is even possible to add some desirable objectives that play also an important role in the process, but they do not have the same relevance compared to the strict goals and constraints of classical MBPC [22].

The goals and constraints that define a fuzzy predictive control problem can be represented by a fuzzy membership function as is shown in Fig. 5. This problem can be solved using the fuzzy decision framework introduced by Bellman and Zadeh [23]. For each instant of time, there exists n fuzzy goals $G_1, G_2, \ldots, G_n$ and m fuzzy constraints $C_1, C_2, \ldots, C_m$. Then, it is possible to define a global objective by intersecting every fuzzy membership function over the time horizons defined in the fuzzy MBPC problem [see (4)]

$$\mu_J = (G_1 \cap \cdots \cap G_n) \cap (C_1 \cap \cdots \cap C_m). \quad (4)$$

It is important to notice that the fuzzy decision framework approach treats goals and constraints similarly, therefore the relative weighting of goals and constraints is restricted by the choice of the fuzzy membership functions.

The optimization must be made for the whole future control sequence and in that case the optimization problem becomes

$$\underset{\Delta u}{\mathrm{Max}}\, \mu_J = \underset{\Delta u}{\mathrm{Max}} (G_1 \cap \cdots \cap G_n) \cap (C_1 \cap \cdots \cap C_m). \quad (5)$$

The maximization of μ_J defines a *fuzzy decision problem*, which consists on achieving the greatest degree in which fuzzy criteria, fuzzy goals, and fuzzy constraints are satisfied simultaneously. For example, if the fuzzy intersection is evaluated using the $\min t$-norm the problem is to maximize the minimum degree of satisfaction among fuzzy goals and fuzzy constraints. The "hardness" of the intersection can be changed choosing a different t-norm.

In order to define the minimization problem, a fuzzy complement is applied to the cost function of (5), resulting in the following equivalent problem:

$$\underset{\Delta u}{\mathrm{Min}}\, \overline{\mu_J} = \underset{\Delta u}{\mathrm{Min}} (\overline{G_1} \cup \cdots \cup \overline{G_n}) \cup (\overline{C_1} \cup \cdots \cup \overline{C_m}). \quad (6)$$

Different operators like the algebraic product, maximum, sum, or other t-norm can be used to make the fuzzy aggregation. The election of the method must consider the desired softness in the control outputs, shape of utilized membership functions and available computational resources. Literature suggests using the Yager operator [24]. This operator is defined by the following expressions:

$$t_{\mathrm{norm}}(a,b) = \max\left\{0, 1 - ((1-a)^p + (1-b)^p)^{1/p}\right\} \quad (7)$$

$$t_{\mathrm{co\text{-}norm}}(a,b) = \min\left\{1, (a^p + b^p)^{1/p}\right\}. \quad (8)$$

The parameter p, $p \in (0, \infty)$, adjusts the degree of the fuzzy aggregation. A greater p represents a "harder" fuzzy aggregation.

In order to compare the minimization problem of (6) with the classical MBPC formulation, membership functions like those of Fig. 5 and the Yager t-norm will be considered [see (7)]. With these considerations, an equivalent problem to the one in (3) can be solved in fuzzy predictive control by minimizing the following objective function:

$$\mu'_J = \sum_{j=N_1}^{N_p} \left(\bar{\mu}_e \left(\hat{y}(t+j|t) - w(t+j)\right)\right)^p + \sum_{j=1}^{N_u} \left(\bar{\mu}_u \left(\Delta u(t+j-1|t)\right)\right)^p \quad (9)$$

and $\mu_J = \min\{1, \mu'_J 1/p\}$.

Because of nonlinearity in the process model and/or the decision function, the optimization problem is usually nonconvex and cannot be solved using standard optimization algorithms such as quadratic programming (QP). In order to solve the optimization problem represented in (9) using a gradient method like sequential quadratic programming (SQP), the Yager operator must be relaxed, not limiting its value to a fuzzy number between 0 and 1; the relaxation consists in modifying expression (7) to consider only the second argument of the maximum operator.

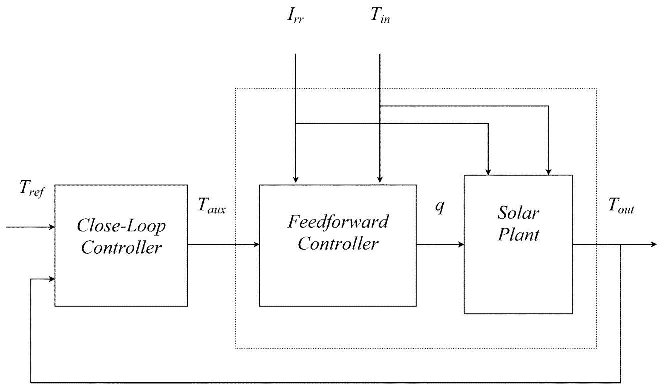

Fig. 6. Feedback-feedforward control system.

TABLE I
MAIN SYSTEM VARIABLES

Symbol	Variable	Unit
T_{ref}	Reference outlet oil temperature	ºC
T_{aux}	Feedforward input temperature	ºC
q	Oil flow (manipulated variable)	l/s
T_{out}	Outlet oil temperature (controlled variable)	ºC
T_{in}	Inlet oil temperature	ºC
I_{rr}	Solar radiation	W/m^2

V. APPLICATION TO THE SOLAR POWER PLANT

A. Problem Statement

The main control goal in the solar plant is to keep the outlet oil temperature as close as possible to a given reference temperature. This should be achieved through changes in the field oil flow, despite the disturbances that affect the system. These disturbances are mainly the solar radiation, the inlet oil temperature and the environment temperature.

In order to apply and compare the controllers described in Sections III and IV to the solar plant, this paper considers a simple predictive controller that uses a linear model around an operation point [3]. This control scheme includes a feedforward controller, shown in Fig. 6, to compensate the effect of measured disturbances, solar radiation, and inlet oil temperature. In addition, the main variables are listed in Table I.

The output of the feedforward controller is calculated from the following expression [3], [18]:

$$q = \frac{0.7869 I_{\rm rr} - 0.485\left(T_{\rm aux} - 151.5\right) - 80.7}{T_{\rm aux} - T_{\rm in}}. \tag{10}$$

The simulation study presented in this paper considers two specific disturbance profiles, which are shown in Fig. 7 [3]. The solar radiation profile varies according to the year season, daytime, and geometry of the distributed collector field. Additionally both disturbances are filtered using a moving-average filter that considers the eight past samples.

B. Classical Predictive Controller

MBPC can be implemented considering a linear model for the combined dynamic system, plant and the feedforward controller (see Fig. 6), for an operation oil flow of 6 l/s. This combined system leads to the following controlled auto regressive with integrated moving average (CARIMA) model [3]:

$$A(z^{-1})T_{\rm out}(t) = B(z^{-1})T_{\rm aux}(t-1) + \frac{e(t)}{\Delta} \tag{11}$$

where $\Delta = 1 - z^{-1}$ and

$$\begin{aligned} A\left(z^{-1}\right) =& 1 - 1.5681 z^{-1} + 0.5934 z^{-2} \\ B\left(z^{-1}\right) =& 0.0612 + 0.0018 z^{-1} - 0.0171 z^{-2} + 0.0046 z^{-3} \\ &+ 0.0005 z^{-4} + 0.0101 z^{-5} - 0.0064 z^{-6} \\ &- 0.015 z^{-7} - 0.0156 z^{-8}. \end{aligned}$$

The sampling period of the model and controller is 39 s. Considering the cost function of (3) the horizon parameters are set to $N_1 = 1, N_p = 15$ and $N_u = 15$. The weights used are $\delta(j) = 1$ and $\lambda(j) = 7$, for j =1 to 15. Although the oil flow is limited to the range 2 l/s to 12 l/s, the study is performed around the operating condition of 6 l/s of oil flow.

In this case, the MBPC algorithm produces the $T_{\rm aux}$ sequence that minimizes the cost function, without considering active constraints. The first value of this sequence is applied to the feedforward controller that calculates an oil flow that takes in account the measured disturbances.

As Fig. 8(a) shows, the classical MBPC follows the outlet oil temperature set-point despite the disturbances profiles (see Fig. 7). It is clear that the system response present some oscillations. Two possible reasons for this behavior are the presence of disturbances and the incomplete dynamic modeling due to a simple linear model obtained through excitation of the plant. For the given disturbance profiles, it is more likely the oscillations are the outcome to the lack of complete dynamic modeling. In fact, this plant exhibits antiresonance behavior [3] as a consequence of resonance modes that are excited when fast responses are required. The characteristic frequencies of these resonance modes are different depending on the operating point. The linear model used for control purposes in this paper takes into account these phenomena when operating near 6 l/s. As it is shown in Fig. 8, oscillations are lesser as the oil flow approaches this value, and higher far from this nominal value.

C. Fuzzy Predictive Controller

The structure of the fuzzy predictive controller is similar to the MBPC presented in Section V, this means the model and horizons are the same. The cost function is given by (9). The Yager t-norm with $p = 2$ is used as fuzzy aggregation operator, and the minimization problem is solved using SQP.

As explained in Section IV, the fuzzy characterization of goals and constraints is achieved with fuzzy membership functions, with $\mu_e(\cdot)$ for the error $ET_{\rm out} = T_{\rm out} - T_{\rm ref}$ and $\mu_u(\cdot)$ for the $T_{\rm aux}$ variation. These functions are defined over the set of possible values for both variables. This is a natural straightforward way to go from classical predictive control to a fuzzy one.

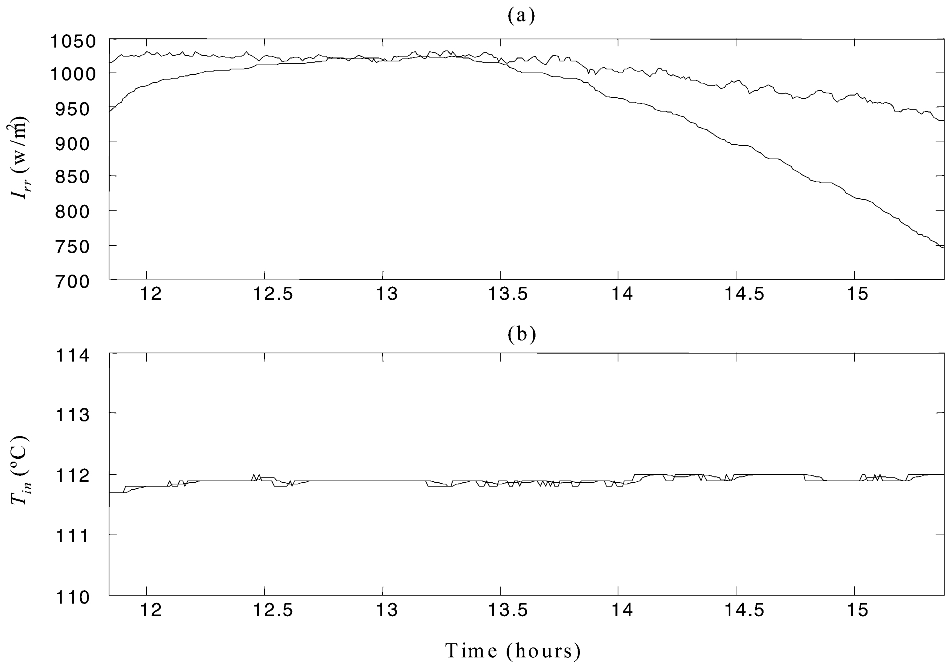

Fig. 7. Disturbance profiles. (a) Solar radiation. (b) Oil inlet temperature.

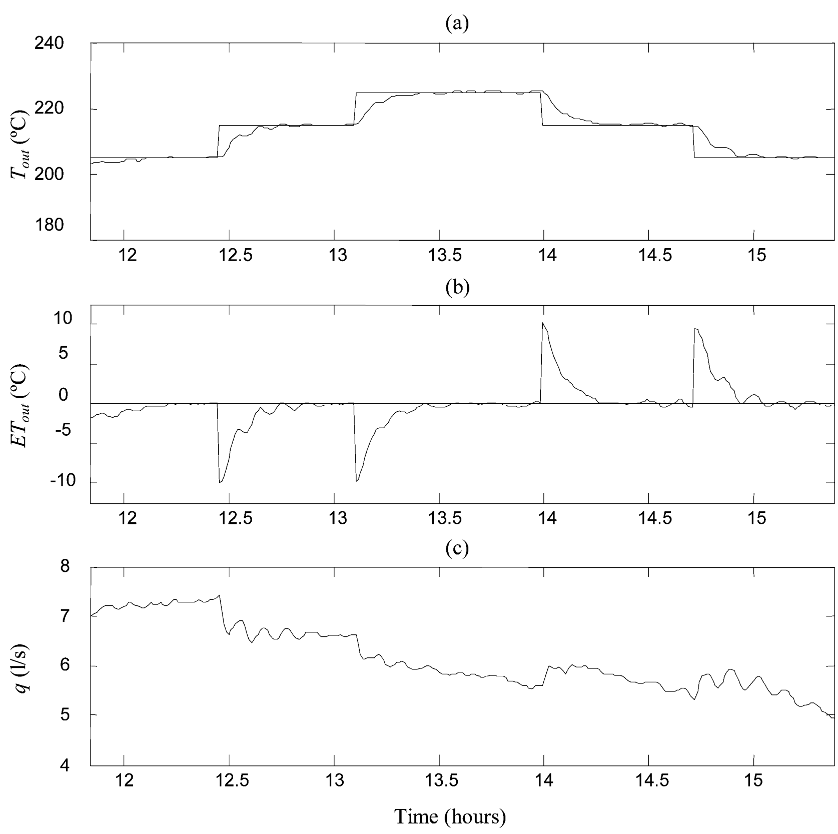

Fig. 8. Simulation results for classical MBPC. (a) Outlet oil temperature. (b) Error in the outlet oil temperature. (c) Oil flow.

A general triangular-shaped membership function is defined by three parameters indicating the inflection points of the function. The following definition will be used:

$$\mathrm{trimf}(x,a,b,c) = \begin{cases} \frac{x-a}{b-a}, & \text{if } a \le x < b \\ \frac{x-c}{b-c}, & \text{if } b \le x \le c \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

The following membership functions will be considered (Fig. 9):

$$\begin{aligned} \mu_e(ET_{\mathrm{out}}) &= \mathrm{trimf}(ET_{\mathrm{out}}, -25, 0, 25) \\ \mu_u(T_{\mathrm{aux}}) &= \mathrm{trimf}(T_{\mathrm{aux}}, -9.5, 0, 9.5). \end{aligned} \tag{13}$$

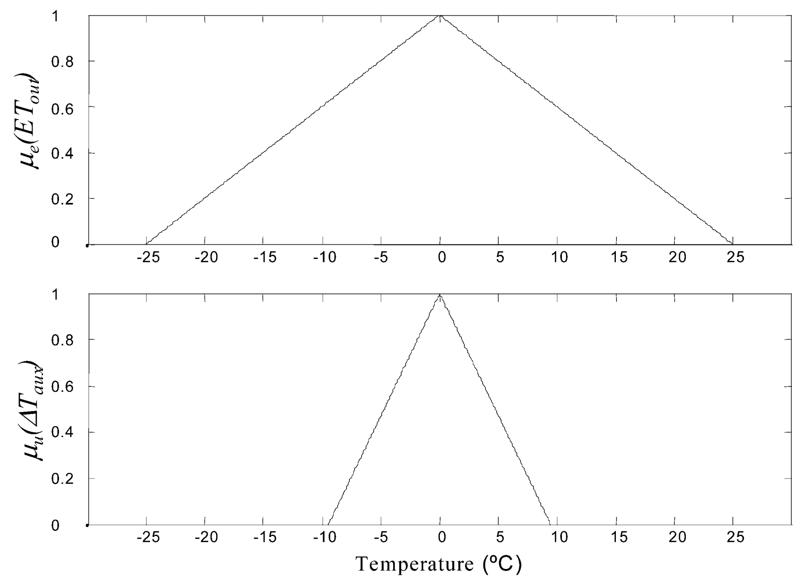

Fig. 9. Triangular-shaped membership functions for T_{out} error and T_{aux} variation.

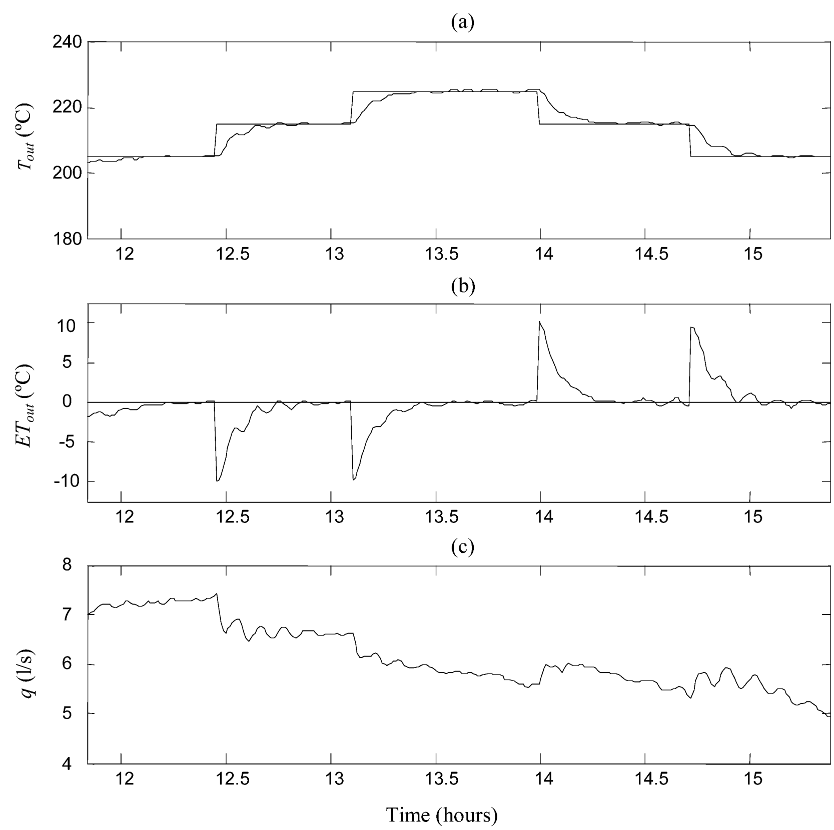

Fig. 10. Simulation results for fuzzy MBPC with triangular-shaped membership functions. (a) Outlet oil temperature. (b) Error in the outlet oil temperature. (c) Oil flow.

The parameters of these membership functions were chosen to replicate the behavior of the classical predictive control with the weights mentioned in Section V and for the considered operation ranges.

The simulation results for fuzzy predictive control with triangular-shaped membership functions are shown in Fig. 10. Comparing Figs. 8 and 10, the responses of the system with either one of the controllers seem to be identical. The explanation to this is the fact that the slopes of the fuzzy membership functions were fixed according to the weights of classical MBPC.

The similarities of both controllers can be further noticed in the histograms shown in Fig. 11, which presents the T_{out} error distribution for both cases.

As it has been mentioned before, model-based fuzzy predictive control offers several degrees of flexibility and one of them is the election of membership functions. In the next paragraphs,

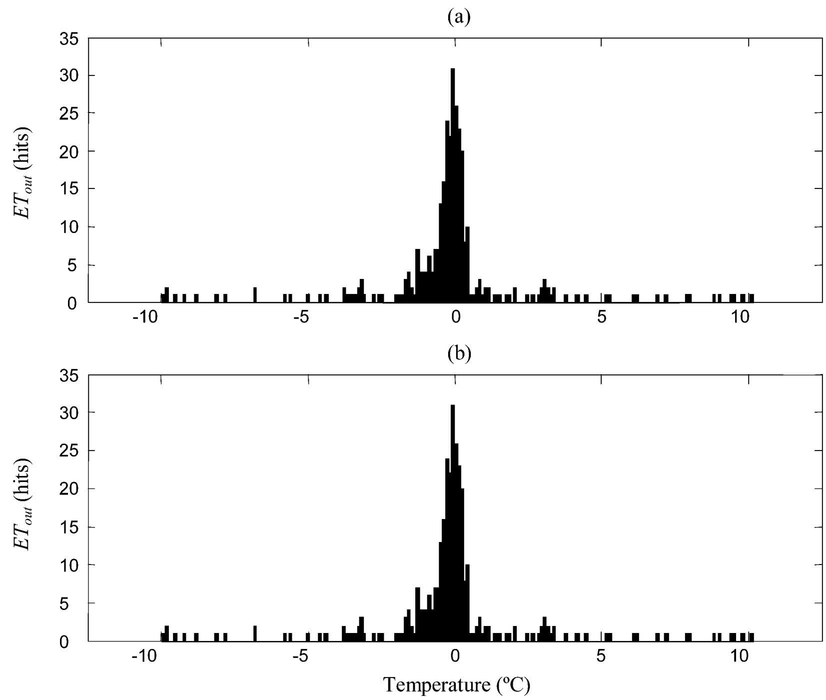

Fig. 11. T_{out} error histograms. (a) Classical MBPC. (b) Triangular-shaped fuzzy MBPC.

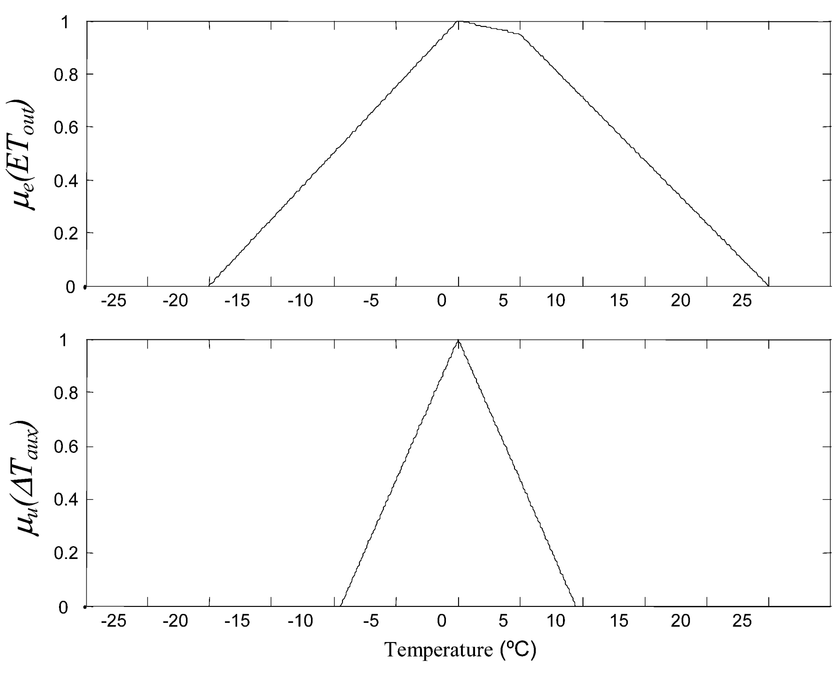

Fig. 12. Custom-shaped membership functions for T_{out} error and T_{aux} variation.

a second controller that uses custom-shaped membership functions is presented.

It will be assumed that one of the goals of the solar power plant is to maximize the heat transfer from the collector field to an unknown load. Under this assumption, the outlet oil temperature set-point is considered to be more strict when the controlled variable is under this reference and not so much in the opposite case (always considering that the maximum temperature will not surpass the physical limits of the installation, 300°C). Unlike the classical MBPC, the fuzzy predictive controller can easily incorporate this kind of control goals.

The membership function for the error in the outlet oil temperature, μ_e, is customized according to (14). The membership function for the oil flow variation is kept identical [see (12) and (13)]

$$\text{cumf}\,(x,a,b,c,d,p) = \begin{cases} \frac{x-a}{b-a}, & \text{if } a \le x < b \\ 1 + \frac{(1-p)(x-b)}{b-c}, & \text{if } b \le x < c \\ \frac{p(x-d)}{c-d}, & \text{if } c \le x \le d \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

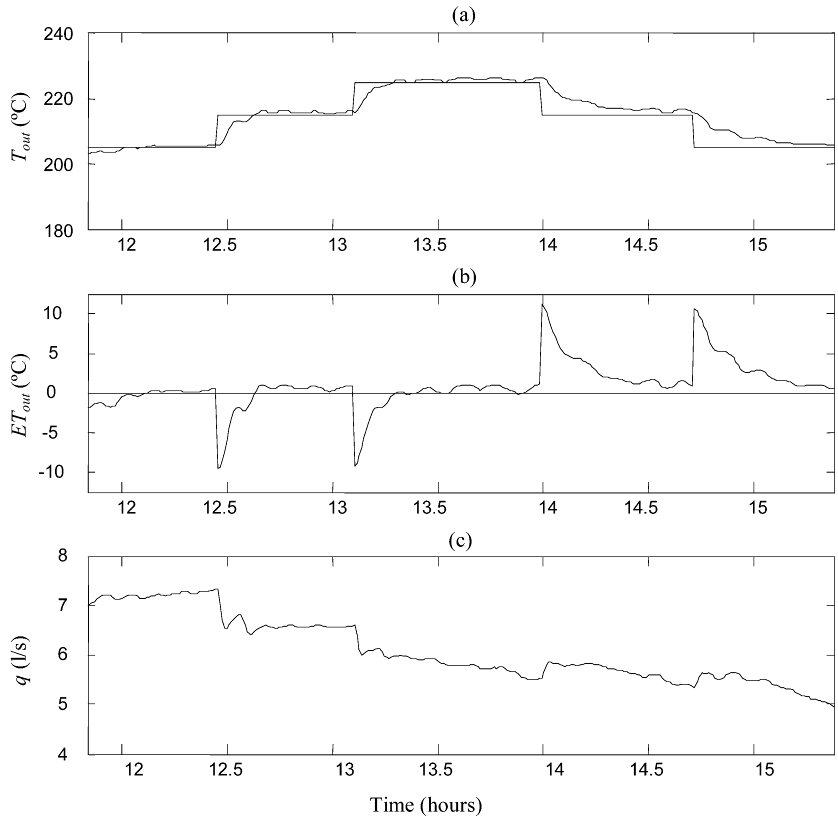

Fig. 13. Simulation results for fuzzy MBPC with custom-shaped membership functions. (a) Outlet oil temperature. (b) Error in the outlet oil temperature. (c) Oil flow.

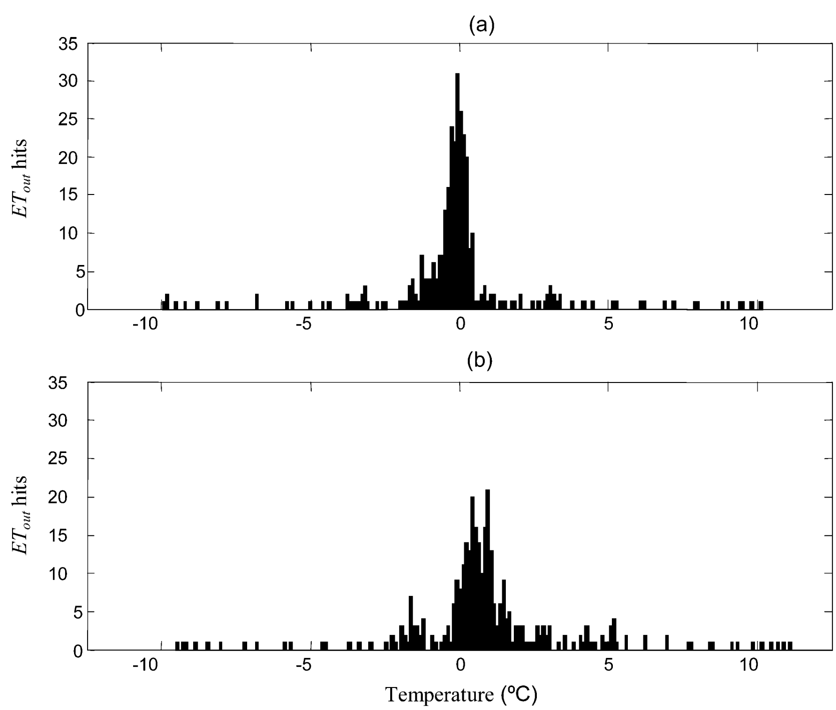

Fig. 14. T_{out} error histograms. (a) Classical MBPC. (b) Custom-shaped Fuzzy MBPC.

New membership functions will be considered (see Fig. 12)

$$\mu_e\left(ET_{\text{out}}\right) = \text{cumf}\left(ET_{\text{out}}, -20, 0, 5, 25, 0.99\right)$$
$$\mu_u\left(\Delta T_{\text{aux}}\right) = \text{trimf}\left(\Delta T_{\text{aux}}, -9.5, 0, 9.5\right). \quad (15)$$

The simulation results for this new fuzzy predictive controller with custom-shaped membership functions are shown in Fig. 13. The response of the plant with this controller is different to the previous two. Comparing these results to those in Figs. 8 and

10, it can be seen that the response times when the set-point is increased are smaller than those when the set-point is decreased. Additionally the manipulated variable, oil flow, is not as oscillatory as with the previous controllers.

After each set-point change there is a positive error that is not present in the previous controllers. This behavior is completely consequent with the fuzzy membership function for the outlet oil temperature error. The modifications on the error profile distribution can be appreciated looking at the error histograms in Fig. 14. According to Fig. 14(b), the reduction of negative error and the increase of positive error in the range 0°C to 5°C are concordant with the shape of the custom membership function μ_e.

VI. Conclusion

In order to apply classical control techniques such as MBPC to real processes, values of several parameters of the objective function and constraint limits must be chosen and sometimes this represents a difficult decision for the control engineer. As an alternative, it has been proposed the use of fuzzy membership functions to represent goals and constraints in a more flexible and transparent way.

A comparison has been made between classical MBPC and the new fuzzy methodology proposed applied to a solar power plant. The results show that under certain circumstances (weights, fuzzy membership functions, and fuzzy t-norm) the solutions of both control algorithms are quite similar.

However, the fuzzy MBPC formulation gives a greater flexibility to characterize the goals and constraints for the process. This fact can be appreciated in the performance of a fuzzy predictive controller based on custom-shaped membership functions.

As concluding remarks of the new methodology proposed we highlight two attributes: 1) It is based on a well-proven successful algorithm such a classical MBPC, and 2) It empowers MBPC with flexibility to consider goals and constraints different to those usually used in classical MBPC. This last remark is the main advantage of fuzzy predictive control. The flexibility provided by the fuzzy membership function and the fuzzy aggregation can be used to consider complex goals such as different weights for distinct error situation as shown in this paper. Other possible complex goals for the solar power plant could be simultaneous fulfillment of conditions in the outlet oil temperature and the oil flow.

Clearly, the possibilities of fuzzy predictive control are enormous and the role of the control engineer is to search for processes suitable for its application.

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