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A survey on control schemes for distributed solar collector fields. Part II: Advanced control approaches

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Abstract

This article presents a survey of the different advanced automatic control techniques that have been applied to control the outlet temperature of solar plants with distributed collectors during the last 25 years. A classification of the modeling and control approaches described in the first part of this survey is used to explain the main features of each strategy. The treated strategies range from classical advanced control strategies to those with few industrial applications.

Keywords: Solar thermal energy; Temperature control; Automatic control

1. Introduction

In the first part of this survey, the main features of solar plants with a distributed collector system (DCS) from the viewpoints of modeling, simulation and basic control have been studied. A classification of control strategies introduced by Seborg (1999) has been considered to classify the different control approaches successfully used to control such kind of plants. This paper is devoted to overview advanced control techniques aimed at taking into account the special dynamic features of distributed solar collectors and the fact that the main source of energy cannot be manipulated and furthermore it changes in a seasonal and on a daily base, acting as a disturbance when considering it from a control point of view. Some of these advanced control disciplines have evolved around the Linear Systems Control Community, as is the case of robust control (RC) or adaptive control (AC), while other disciplines have developed around the Artificial Intelligence (AI) Control Community, as is the case of knowledge based systems (KBS) also called "expert systems", neural network controllers (NNC) and fuzzy logic controllers (FLC). Many of the applications included in this paper have been tested in the Acurex field of the Plataforma Solar de Almería (PSA, South-East Spain), see part I of this survey for a complete description.

2. Model-based predictive control (MPC)

Many different model-based predictive control (MPC) strategies (Fig. 1) have been applied to control DCS. The ideas appearing in greater or lesser degree in all the predictive control family are basically (Camacho and Bordons, 2004): explicit use of a model to predict the process output at future time instants (horizon), calculation of a control

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Nomenclature

AC	adaptive control
AI	artificial intelligence
ANN	artificial neural network
ARMAX	autoregressive moving average models with exogenous inputs
ARX	autoregressive models with exogenous inputs
DCS	distributed collector system
FAM	fuzzy associative memory
FF	feedforward
FIR	finite impulse response
FL	feedback linearization
FLC	fuzzy logic controller
GPC	generalized predictive control
GS	gain scheduling
HGA	hierarchical genetic algorithm
IMC	internal model control
IPD	integral proportional derivative
KBS	knowledge based system
LQG	linear quadratic gaussian
LS	least squares
LTR	loop transfer recovery
MPC	model-based predictive control
MRAC	model reference adaptive control
MUSMAR	multivariable self-tuning multipredictor adaptive regulator
NC	nonlinear control
NMPC	nonlinear model predictive control
NNC	neural network controllers
OR	output regulation
PDE	partial differential equation
PID	proportional integral derivative
PSA	Plataforma Solar de Almería
QFT	quantitative feedback theory
RBF	radial basis function
RC	robust control
SMC	sliding mode control
STC	self-tuning control
TDC	time delay compensation
VSCS	variable structure control system

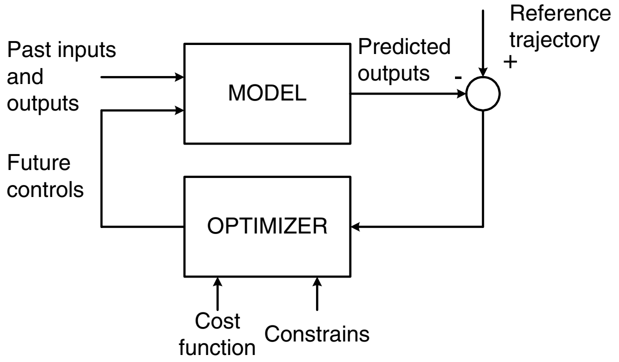

Fig. 1. Block diagram of a model-based predictive controller (MPC).

sequence minimizing a certain objective function and receding strategy, so that at each instant the horizon is shifted towards the future, which involves the application of the first control signal of the sequence calculated at each step. Most of the MPC strategies applied to the control of DCS are in adaptive, robust, or nonlinear fields and including a feedforward term as a part of the controller (Berenguel, 1996; Camacho et al., 1997b). Few implementations of MPC controllers with fixed parameters have been reported in the literature (e.g. Camacho and Berenguel, 1993; Camacho et al., 1994a, 1997b). The most important applications are: MPC adaptive control, treated in the next section (Camacho and Berenguel, 1993, 1994a; Camacho et al., 1994a; Meaburn and Hughes, 1996; Coito et al., 1996, 1997; Silva et al., 1997; Rato et al., 1997a,b, 1998; Stuetzle et al., 2004), MPC gain scheduling control (Camacho et al., 1994b; Berenguel et al., 1996; Lemos et al., 2000), MPC robust control (Camacho and Berenguel, 1997; Pérez de la Parte et al., 2007) and MPC nonlinear control, including NNC and feedback linearization (FL) approaches (Camacho and Berenguel, 1994b; Arahal et al., 1997, 1998a,b; Berenguel et al., 1997b, 1998; Pickhardt and Silva, 1998; Silva, 1999b,c; Pickhardt, 2000a; Silva et al., 2003a,b; Jalili-Kharaajoo and Besharati, 2003). Many of these are treated in the next sections.

3. Adaptive control (AC)

The main idea behind AC is to modify the controller when process dynamic changes. It can be said that adaptive control is a special kind of nonlinear control where the state variables can be separated into two groups moving in two different time scales. The state variables which change faster, correspond to the process variables (internal loop), while the state components which change more slowly, correspond to the estimated process (or controller) parameters. Adaptive controllers have traditionally been classified into one of the following families: model reference adaptive controllers (MRAC, Fig. 2a) and self-tuning controllers (STC, Fig. 2b) (Aström and Wittenmark, 1989).

As has been mentioned, when controlling DCS, the control schemes that vary the oil flow rate applied to the collector field generally utilizes a combination of feedback and feedforward control, incorporating a nonlinear mechanism to operate effectively. Initial studies conducted on the Acurex field attributed the oscillatory behaviour obtained with classical proportional-integral-derivative (PID) controllers to the variability of plant dynamics with operating point

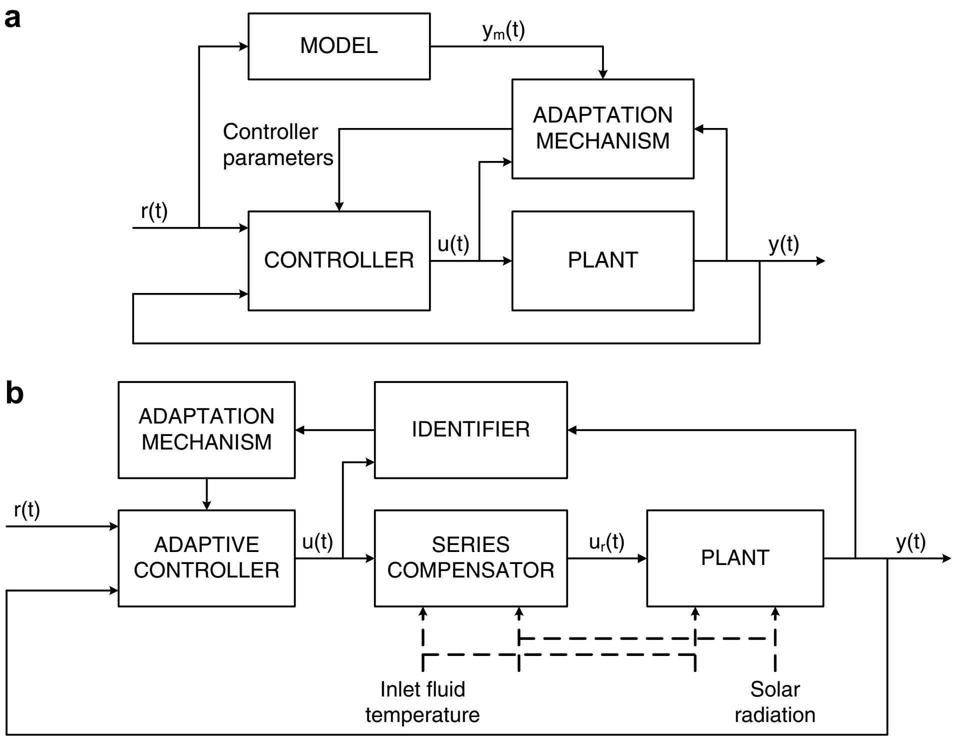

Fig. 2. Block diagrams of adaptive control (AC) schemes. (a) Model reference adaptive control (MRAC), (b) self-tuning controller (STC).

(Rubio, 1985; Rubio et al., 1986, 1989, 2006; Camacho et al., 1992). Different adaptive control schemes were thus developed to cope with this problem of changing dynamics. The major role played by changes of solar radiation and plant uncertainty lead to the approach of Camacho et al. (1992) where a pole placement self-tuning PI controller with a series feedforward compensator is used, also using a modified recursive least squares (LS) identification mechanism and low order discrete transfer functions representing plant dynamics, as on-line estimation based upon high order transfer function models tends to perform poorly with slow parameter convergence being the norm. Thus, lower order transfer function models have been used when desirable control bandwidths are not too stringent, but decreasing the commissioning time of the controller and producing a simple control law. Simulation results prove the advantage of the adaptive controller above a fixed PI controller. The same feedforward term and identification mechanism were then embedded within an adaptive predictive control scheme providing very simple control laws (Camacho et al., 1994a). In Camacho and Berenguel (1997), an adaptive robust predictive controller is developed based on a simplified transfer function model of the plant, where the pole location if fixed and the parameters of the numerator are on-line robustly identified, in such a way that the uncertainty of the closed loop system decreases quickly. The reference tracking for the final operating-point is good, however, for changing radiation and inlet oil temperature the outlet temperature shows offset. It should be mentioned that all controllers discussed so far contain a series feedforward compensator. This means that the output of the applied controllers is not the oil flow but the temperature setpoint for this series compensator that already to some degree moderates the nonlinear plant characteristics. Different forms of the multivariable self-tuning multipredictor adaptive regulator MUSMAR (Greco et al., 1984) were also demonstrated with success (Coito et al., 1996, 1997; Silva et al., 1997; Rato et al., 1997a,b). In Silva et al. (1998), Rato et al. (1998) and Silva (1999a), a new dual version of the MUSMAR algorithm is presented based on a bicriterial optimization, in order to improve start-up transients. The adaptive MUSMAR controller proposed in Coito et al. (1996, 1997), which includes the accessible disturbances from the radiation and the oil inlet temperature shows good results especially for experiments at rapidly changing values for the radiation. However, the complexity of this controller is also quite high. Many of the proposed adaptive control schemes show oscillatory behaviour when requiring fast responses to setpoint changes and disturbances. Meaburn and Hughes (1993b) established that the cause of these problems was the existence of resonance dynamics lying at a low frequency. A simple linear transfer function model of these characteristics was developed by Meaburn and Hughes (1993a, 1994) from a system representation derived from its basic thermodynamic equations. Using this model, a series cancellation controller was developed, which in simulation studies achieved faster control than a PI controller, whilst maintaining a similar level of damping. However, the controller was seen to oscillate the input signal vigorously. This controller was tuned using experimental frequency response data and implemented as a prescheduled scheme (Meaburn, 1995). This controller, when combined with feedforward, was shown to be capable of effectively regulating the outlet temperature during both irradiance and inlet temperature disturbances. In Berenguel and Camacho (1995, 1996), an application of frequency-based internal model control (IMC) for accounting the anti-resonance characteristics is developed. The key idea of the method is to implement both the model of the plant and the controller with frequency-based interpolation models, in such a way that a determined frequency response of the controlled system is imposed at the chosen interpolating points. In the frequency-based IMC control structure, the error signal is fed to a bank of comb filters where it is separated into its spectral components. Each of the components is then multiplied by a complex gain and fed to the process and model. In order to implement the frequency-based adaptive controller, the frequency response of the plant is needed at all interpolating points; this can be obtained by using banks of band filters for the input and output of the plant. For the estimation of the parameters describing these simple models of the plant in each interpolating frequency, a common recursive LS algorithm was used. With this approach, the problem of identifying high-order polynomials is decomposed into a few simple problems in which only low-order models need to be identified.

4. Gain scheduling (GS)

Some controllers have the ability of adapting to changes in process dynamics but are not considered to be proper adaptive controllers. This is the case of gain scheduling (GS) controllers (Fig. 3), where process dynamics can be associated to the value of some process variables that can be measured related to the operating point or to environmental conditions. If the dynamic characteristics of the process can be inferred from measurable variables, the controller parameters can be computed from these variables. Notice that only the inner loop appears in this control structure and the parameter updating can be considered as a sort of feedforward term which changes controller gains.

Explicit recognition of plant nonlinearities and their exploitation could lead to performance and robust stability improvements, but at the cost of increasing the controller complexity. Due to the presence of antiresonance modes, conventional discrete transfer functions must be around tenth order to represent the resonance dynamics of DCS. Scheduling avoids the problems that arise when using AC with high order models. First steps in this direction were made by employing gain scheduling control using high order models of the plant (Camacho and Berenguel, 1993; Camacho et al., 1994b; Meaburn and Hughes, 1994, 1995; Johansen et al., 2000; Pickhardt, 2000b), switched multiple model supervisory controllers (Lemos et al., 2000) and nonlinear predictive control. In Camacho et al. (1994b) and Berenguel et al. (1996), high-order discrete plant autoregressive models with exogenous inputs (ARX) were used for four operating conditions defined by fluid flow values (as the feedforward in series was used) and based on this model, the parameters of a generalized predictive controller (GPC) are determined. The experimental results show a quite good reference tracking without an offset of the output temperature (Fig. 4). An adaptive gain-scheduled linear quadratic design approach, also based on local linear ARX models depending on oil flow conditions, was investigated by Pickhardt (1998). A control strategy based on switching between multiple local linear models/controllers was suggested and tested by Rato et al. (1997b), using the MUSMAR adaptive algorithm in the design of the controllers, considering the properties of this algorithm as far as nonlinearities and unmodeled dynamics. The control structure consists in a bank of candidate controllers and a supervisor. Each of the candidate controllers is tuned in order to match a region in the plant operating conditions. The MUSMAR adaptive controller is applied off-line to a plant model corresponding to the operating condition considered. The candidate controller gains are obtained as the MUSMAR convergence gains. The supervisor consists of a shared-state estimator, a performance weight generator and a time switching logic scheme. In Nenciari and Mosca (1998), supervised linear quadratic gaussian (LQG) multicontrollers were developed, where third order ARX models were identified for six oil flow conditions. Simpler approaches as that presented in Vaz et al. (1998) can be also found, where a PID controller with gain interpolation is developed. Johansen et al. (2000) elegantly showed that gain-scheduling can effectively handle the plant nonlinearities, using high-order local linear ARX models that form the basis for the design of local linear controllers using pole placement and flow rate and solar radiation as scheduling variables. They also pointed out that slow variation of the scheduling variables is a sufficient condition for stability of gain-scheduled control, but the input used for scheduling in the solar plant varies at approximately the same rate as the output, thus stability is proven by experiments. Results in this work are similar to those in Camacho et al. (1994b) and better than those in Pickhardt (1998) and Rato et al. (1997b), as more accurate higher-order local models are used while the lower order models used in Pickhardt (1998) and Rato et al. (1997b) cannot be expected to capture the

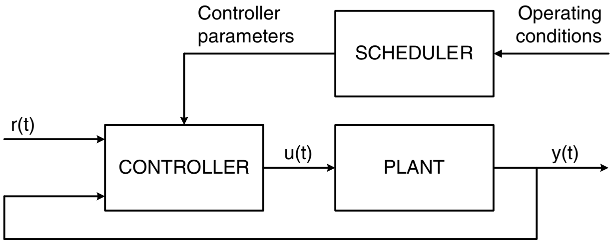

Fig. 3. Block diagram of gain scheduling (GS) controllers.

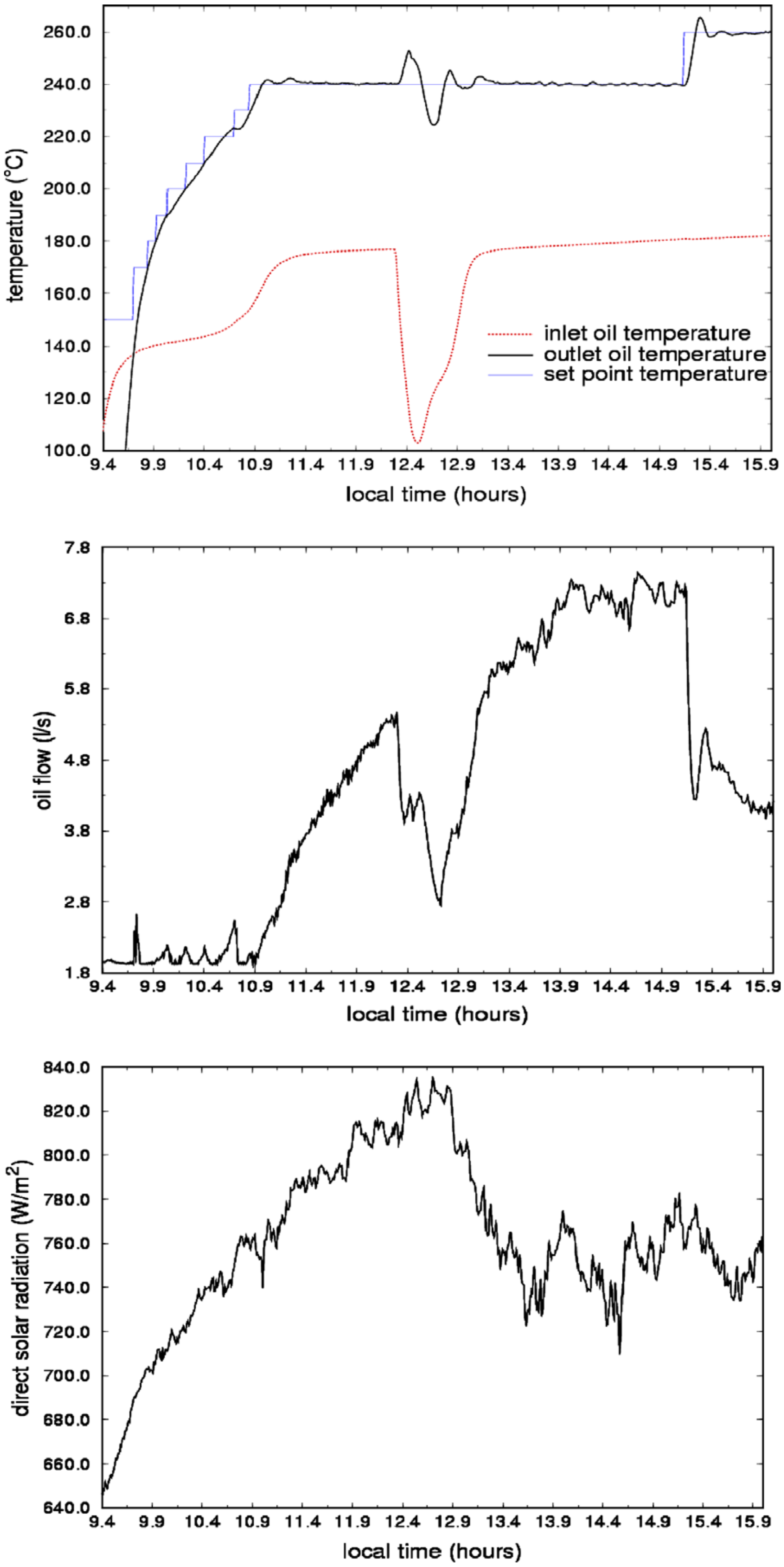

Fig. 4. Experimental results with a GS GPC controller in the Acurex DCS (June 12th, 1995).

antiresonance modes. Another reason is that the local controllers are scheduled on the actual oil flow rate rather than the predicted steady-state oil flow rate, as in Pickhardt (1998), or local model performance measures, as in Rato et al. (1997b), both of which correspond to lower bandwidth in the scheduler. In Pickhardt (2000b), the application of indirect adaptive control (LQG controller) is shown. The region of operation is split up into five operating-points which are represented by five different dynamical linear third-order autoregressive moving average with exogenous inputs (ARMAX) models to describe the plant characteristics. The actual operating-point of the plant is determined by a characteristic value combining several measurements. The algorithm contains an online identification procedure to determine and to update the respective model of the operating-point. If the operating conditions change slowly, a soft transition between the different operating points is carried out. In Henriques et al. (1999a,b), a hierarchical control strategy consisting on a supervisory switching of PID controllers, simplified using the c-Means clustering technique is developed, providing real results. 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 is tuned off-line, by the combination of a dynamic recurrent nonlinear artificial neural network (ANN) model with a pole placement control design. Stirrup et al. (2001) developed a control scheme that employs a fuzzy PI controller, with feedforward, for the highly nonlinear part of the operating regime and gain scheduled control over the more linear part of the operating envelope, only showing simulation results based on the model developed in Berenguel et al. (1994). In Gil et al. (2002a) and Henriques et al. (2002a), a hybrid scheme is presented combining the potentialities of ANN for approximation purposes with PID control. As in other gain scheduling control schemes, the oil flow is considered as the main variable governing the switching of the controller, but to account for the other variables affecting this value, the scheduling variable is obtained from an ANN having as inputs the values of solar radiation, inlet oil temperature and reference (or outlet) temperatures. Thus, the scheduler implements an inverse of the plant at steady state and uses this signal to select the adequate PID controller.

5. Internal model control (IMC)

The basic structure of an IMC controller is shown in Fig. 5. If there are no modeling errors and there are no external disturbances ($q = 0$), the output (y) of the plant coincides with the output of the model ($\hat{y}$) and as there is no feedback signal, then the controller can be designed in an open loop manner and the resulting control structure is stable if and only if, the process is open loop stable and the controller is also stable. The feedback signal is included to account for uncertainties and disturbances. IMC (Morari and Zarifiou, 1989) has the advantages of open-loop (the controller is easy to design) and closed-loop design methods (the feedback signal in this structure represents the uncertainty about the process and the disturbances). In Farkas and Vajk (2002a,b), a model based on nonlinear partial differential equations (PDE) was developed and used as a part of the control design along with its realizable inverse (static version of the model) as the controller. The IMC design procedure generally consists of two steps: the feedforward controller designed for the nominal model and the controller is tuned by an extra filter to meet the robustness requirements As has been mentioned in Section 3, in Berenguel and Camacho (1995, 1996), a frequency-based IMC for controlling systems with antiresonance characteristics is presented.

6. Time delay compensation (TDC)

Time delay compensation (TDC) schemes (Fig. 6) aim at designing controllers without taking the pure delay of the plant into account and expecting the closed loop response after the delay to be that expected from the design without considering the delay in the dynamics of the process. Several TDC schemes have been developed for controlling DCS. In Meaburn and Hughes (1996), an alternative control scheme using a simplified transfer function model including the resonance characteristics was developed. This controller adopts a parallel control structure similar to that of a Smith predictor. This parallel structure is shown to effectively counter the resonance dynamics of the system whilst avoiding the excitable control signal of the controller developed by Meaburn and Hughes (1993b, 1994). In Normey-Rico et al. (1998), an easy-to-use PI controller with dead-time compensation that presents robust behaviour

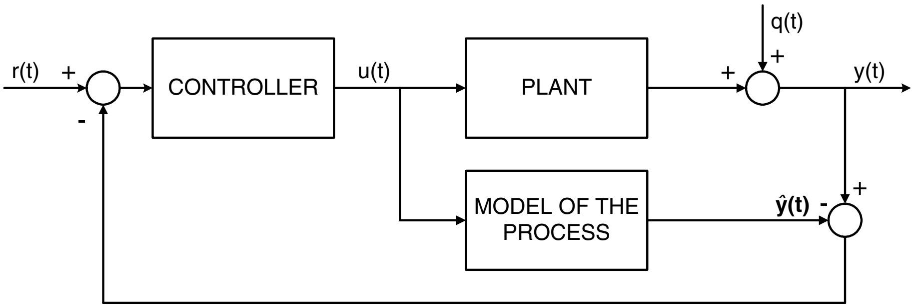

Fig. 5. Block diagram of internal model controllers (IMC).

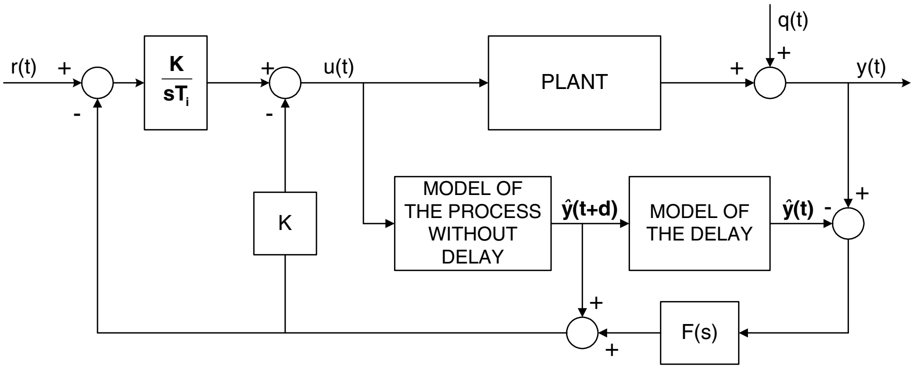

Fig. 6. Block diagram of time delay compensators (TDC).

and that can be applied to plants with variable dead-time is applied to control the Acurex field. The formulation is based on an adaptive Smith predictor structure plus the addition of filter acting on the error between the output and its prediction in order to improve robustness (Fig. 6). The implementation of the control law is straightforward as the controller has only three tuning parameters that can be tuned using a classical step identification test and the filter needs no adjustment.

7. Optimal control (LQG)

LQG optimal control was an important precursor to the development of the MPC techniques that are now widely used. This method is based on conventional hypothesis: the system is linear, the criterion quadratic and the random disturbances are gaussian. A separated solution to the problem is given: firstly a state estimation is obtained by an observer in the deterministic case or by a Kalman filter in the stochastic one. A linear control law is applied to this estimation which is fed back and with this the complete regulator is obtained. However, the method was extremely sensitive to imprecision in the parameters and to structural modifications. In order to solve the problems presented by the deterioration of robustness caused by the introduction of the observer the method known as LQG with loop transfer recovery mechanism (LQG/LTR) can be used. This method aims at using the analytical possibilities of LQG (and in consequence the use of the computer in aided-design) but modifying the Kalman filter (observer), so that the harmful effects on the robustness (on the stability margins) are attenuated.

In the framework of controlling DCS, Rorres et al. (1980) and Orbach et al. (1981) suggested an optimal control formulation where the objective is to maximize net produced power when the pumping power is taken into consideration. An alternative approach is taken by Carotenuto et al. (1985, 1986), where a quadratic control Lyapunov function is formulated for the distributed parameter model and a stabilizing control law is derived. In Rubio et al. (1996), a LQG/LTR controller and series feedforward controller was developed to obtain a robust fixed parameters controller, able to acceptably control the distributed solar collector field under a wide range of operating conditions (Fig. 7). A similar approach to that of Carotenuto et al. (1986) was developed by Johansen and Storaa (2002a,b), but relies on using a storage function with a physical interpretation leading to a conceptually simpler stabilizing control law with more transparent tuning parameters and less involved analysis. In Willigenburg et al. (2004a,b), a finite dimensional approximation of the physical description of the system is used to control the plant. Despite the high dimension of the model, the digital optimal reduced-order controller design procedure enables to synthesize an optimal controller with just one state variable. The synthesis of the digital optimal reduced-order controller takes place at two levels. At the first level, based on the full nonlinear model representing the finite-difference approximation, the associated initial state and the cost function to be minimized, a digital optimal control is computed, as well as the associated state trajectory and output trajectory; this computation being performed off-line. At the second level, based on the linearized dynamics about the digital optimal control and state trajectory computed at the first level, a quadratic cost function and a description of the model and measurement uncertainties by small additive white noise, a digital optimal reduced-order LQG compensator is computed. This compensator is used to attenuate on-line errors.

8. Nonlinear MPC techniques (NMPC)

Because the majority of controlled processes have inherently nonlinear behaviour, there are incentives to develop MPC control strategies based on nonlinear process models, both obtained from physical principles or data (mainly black box models based on ANN (see Kalogirou, 2000, 2001) for a comprehensive review of applications of ANN in renewable energy systems). In these cases, a nonlinear programming problem must be solved in real time at every sampling period instead of the quadratic linear problem typical of standard MPC. The main difficulties of these methods are that the theoretical analysis of properties of the closed loop such as stability and robustness is very

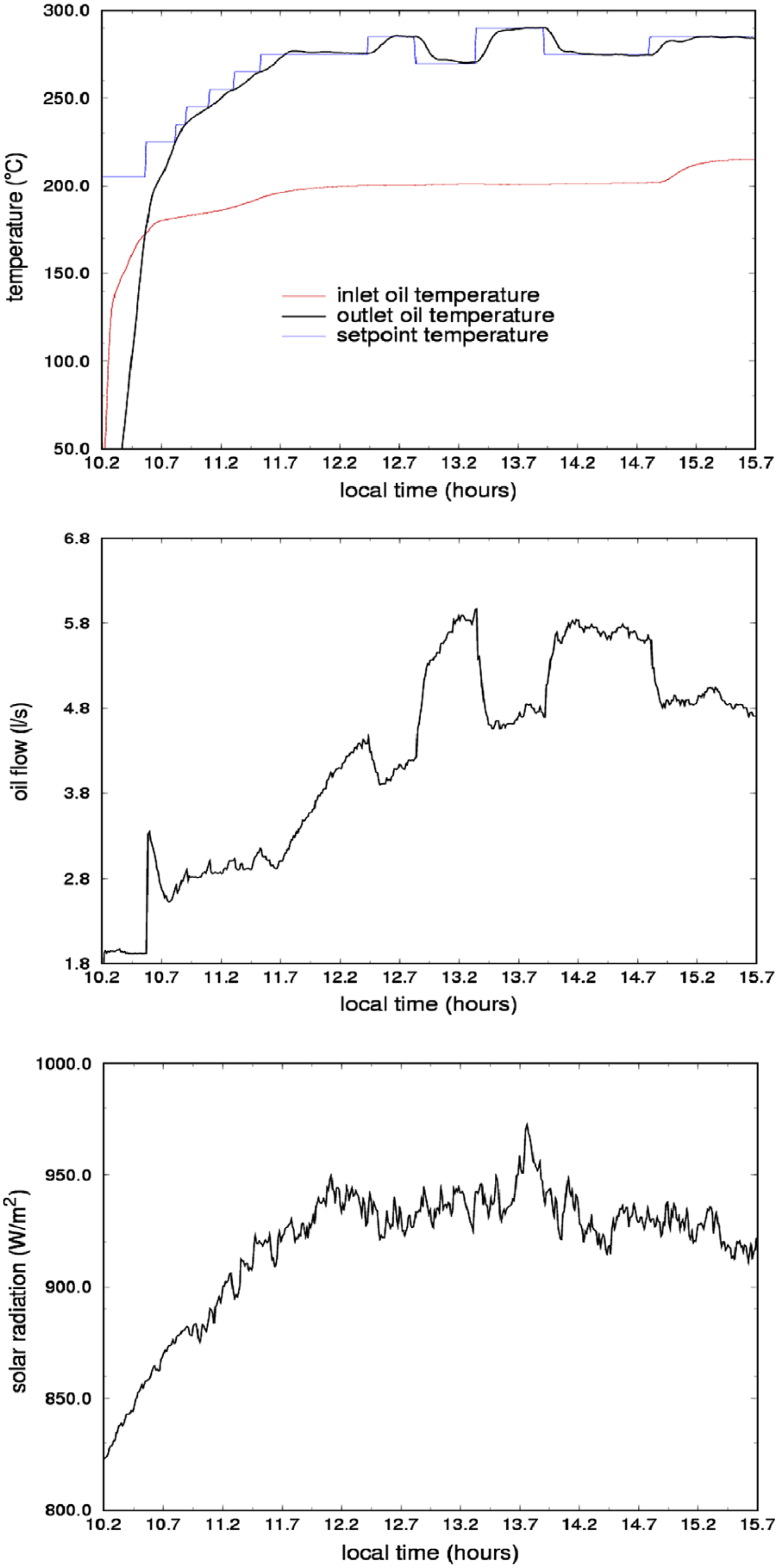

Fig. 7. Experimental results with a LQG/LTR controller in the Acurex DCS (September 19th, 1995).

complicated because of the appearance of nonlinear models in the formulation (application or simulation examples are, therefore, usually used which do not guarantee the generality of the results or are not representative of them) and that if the solution of solving a nonlinear programming problem at each sampling period is adopted, it is difficult to guarantee the convergence of the algorithm in an adequate lapse of time.

Camacho and Berenguel (1994b) presented a MPC control scheme where the response of the plant is divided into the forced and free terms. This division allows the use of a linear model for the forced response, from which the optimal sequence of control actions is obtained without a need for numerical methods. Also, the effect of disturbances is taken into account, thanks to a nonlinear model of the free response. Berenguel (1996) used a nonlinear model based on first principles to obtain the free response of the plant and (Arahal et al., 1998b) an ANN. In Pickhardt and Silva (1998) and Pickhardt (1999, 2000a), a nonlinear model-based predictive controller (NMPC) is developed using a simplified mathematical model of the plant and a search strategy minimizing a cost function for a given prediction horizon. The parameters of the nonlinear model are estimated on-line in order to compensate for time-varying effects and modeling errors. In Gil et al. (2002b), a nonlinear adaptive constrained MPC scheme is presented where the methodology exploits the intrinsic nonlinear modeling capabilities of nonlinear state-space ANN and their online training by means of an unscented Kalman filter. In Gil et al. (2002a,b), another nonlinear adaptive constrained MPC scheme with steady-state offset compensation is developed and implemented.

9. Nonlinear control (NC)

As has been mentioned, explicit recognition of plant nonlinearities and their exploitation could lead to performance and robust stability improvements, but at the cost of increasing the controller complexity. Steps in this direction were made by employing traditional nonlinear control strategies where nonlinear transformations of input or output variables take place. In Barão (2000) and Barão et al. (2002), a FL scheme is proposed including Lyapunov based adaptation and using a simplified plant model. For dealing with plant nonlinearities and external disturbances, a nonlinear transformation is performed on the accessible variables such that the transformed system behaves as an integrator, to which linear control techniques are then applied. In Johansen and Storaa (2002a,b), a control design is proposed based on a distributed model, using ideas from passivity theory, that is to use internal energy as a storage function and then use energy considerations and Lyapunov-like arguments to derive stable and robust control laws relying on feedback from the distributed collector field's internal energy. It is shown that if the internal energy is controlled, the outlet temperature is under control as well. In order to achieve passivity and high disturbance rejection performance, the design also incorporates feedforward from the measured disturbances. In Silva et al. (2002c), a PDE physical plant model is used for nonlinear control purposes. Two situations are considered: in the first, a constant space discretization is imposed; this causes the sampling period to vary according to the flow; in the second, both a constant sampling in space and time cause temperature to be a function of flow and solar radiation; linearizing this function by a convenient variable transformation suggests the use of FL techniques. The first considered situation is exploited in Silva et al. (2003a,b), where the key point is the observation that the value of oil flow establishes a "natural" time scale for the system. This is achieved in discrete time by indexing the sampling rate to the value of flow. As a consequence, the model equations become linear and it is possible to achieve good performance on step responses of big amplitude. In the approach followed by Igreja et al. (2003), the PDE describing the field is approximated by a lumped parameter bilinear model, whose states are the temperature values along the field. By using feedback exact linearization together with a Lyapunov's approach, an AC is designed. This paper improves the previous work of Barão et al. (2002) by using a better approximated model which takes into account that, in the field considered, temperature measures are only made at the input and at the output and not along the pipe. In Cirre et al. (2005a), an automatic control approach using a simple FL method and a lumped parameter model of a DCS is also developed. The control scheme resembles that of a feedforward controller in combination with a classical feedback controller as those presented in Camacho et al. (1992), but with the difference that an embedded feedback from the output is used both for linearization and feedforward purposes. The model used to perform the nonlinear mapping in the FL scheme was improved when compared to existing ones to account for the varying delays between the inlet and the outlet temperatures, what is of great relevance in order to improve the performance of the model during the start up stage and when disturbances in the inlet oil temperature occur, where other models fail to reflect the real dynamical behaviour. This simplified physical model has been used to design an input–output FL controller where the design of the controller is performed on a linear representation of the system as the nonlinear dynamics are embedded in the definition of a virtual control signal. Conditions for the existence of a FL controller are fulfilled always that the inlet and outlet oil temperature are different, what is always true during nominal operation and is assured during the start up stage by replacing the real outlet oil temperature by the reference temperature, thus helping to improve the dynamical response of the system during this phase. Any linear controller could be used in the design of the linear part of the control system. In this work, an integral-proportional-derivative (IPD) with anti-reset windup controller was chosen and implemented at the real plant. All the control schemes based on FL have shown excellent results when tested at the real plant and are very adequate for the starting up phase of the operation. In Henriques et al. (2002b), an ANN based indirect adaptive control scheme is developed. The output regulation (OR) theory aims to derive a control law such that the closed loop system is stable and, simultaneously, the tracking output error converges to zero. This technique leads to a straightforward method for solving nonlinear control problems. However, the OR theory assumes perfect model knowledge. Given the ANN model plant mismatch, an on-line adaptation of ANN weights is considered in order to improve the discrepancies between the output of a previous off-line model and the actual output of the system. By means of a Lyapunov analysis stability condition for the weights updating is employed.

10. Robust control (RC)

Robust control tries to apply principles and methods that allow the discrepancies between the model and the real process to be explicitly considered. There are many techniques for designing feedback systems with a high degree of robustness, some of which are commented in Camacho et al. (1997b) in the scope of the control of solar plants. In Section 7, the application of a robust optimal LQG/LTR control scheme (Rubio et al., 1996) has been commented. Based on the quantitative feedback theory (QFT), in Cirre et al. (2003) a robust controller was developed incorporating a series feedforward controller to solve a simplified problem in which a nonlinear plant subjected to disturbances is treated in the design as an uncertain linear plant with only one input (the reference temperature to the feedforward controller). The frequency response of the plant was analysed for different operating points using dynamic tests performed on the simulator of the field (Berenguel et al., 1994). In this way, in the process design of the QFT controller, the disturbances affecting the plant are not explicitly taken into account, as the feedforward term partially compensates them. A set of plant models were obtained and used to design a robust controller to maintain the desired response within specific frequency domain bounds and taking into account the uncertainties of the system in the process design. In Ortega et al. (1997), a controller based on the H_∞ theory was developed and successfully tested at the Acurex field. The approach used in this work takes advantage of the assurance of high stability margins in the face of a norm bounded perturbation and uses the feedforward controller in series with the developed controller. One particular approach to robust control design is the so-called sliding mode control methodology which is a particular type of variable structure control system (VSCS), that are characterized by a suite of feedback control laws and a decision rule (termed the switching function) and can be regarded as a combination of subsystems where each subsystem has a fixed control structure and is valid for specified regions of system behaviour. In sliding mode control, the VSCS is designed to drive and then constrain the system state to lie within a neighbourhood of the switching function. In Pérez de la Parte et al. (2007), the application of three predictive sliding mode controllers is presented (reaching law approach, equivalent control approach and a nonlinear GPC law that forces the reachability of a differential predicted surface), using a first order plus dead time model for controller tuning purposes. Thanks to a predictive strategy, these control laws provide optimal performance, even in presence of constraints that cannot be considered in the classical sliding modes theory.

11. Fuzzy logic control (FLC)

Fuzzy logic provides a conceptual base for practical problems where the process variables are represented as linguistic variables which can only present a certain limited number of possible values and that then be processed using a series of rules. FLC seems to be appropriate when working with a certain level of imprecision, uncertainty and partial knowledge and also in cases where the knowledge of operating with the process can be translated into a control strategy that improves the results reached by other classical strategies.

In the framework of this type of systems, FLC has attracted much attention since it was firstly applied to the control of DCS (Rubio et al., 1995). In this seminal work, a direct FLC was developed incorporating a feedforward term (Camacho et al., 1992), aimed at finding a nonlinear control surface to control the output temperature of the field, using previous knowledge about the system. In this case, a special subclass of fuzzy inference systems, the triangular partition and triangular partition with evenly spaced midpoints was used to obtain adequate control signals in the whole range of possible operating conditions. A FLC is commonly described by a set of fuzzy rules that constitute the control protocol. With these rules, the interconnected relationships between measurable variables and control variables can be expressed. In Fig. 8a, three parts can be seen which constitute the design parameters of the FLC: the block fuzzifier, the control block (fuzzy rule base and inference procedure) and the block defuzzifier. The fuzzification interface converts the numerical values of the input variables into linguistic variables (fuzzy sets). The conversion requires scale mapping that transforms the range of values of input variables into corresponding universes of discourse. The rule-based fuzzy control algorithm provides definitions of linguistic control rules which characterize the control policy. The block includes decision making logic, which infers fuzzy control actions employing fuzzy implication and the inference rules. The defuzzification block converts the inferred control action, which interpolates between rules that are fired simultaneously, to a continuous signal. The control scheme uses the error between the output of the plant and the setpoint signal and its increment as inputs for the FLC. The output variable of the FLC is the increment in the control signal (reference temperature

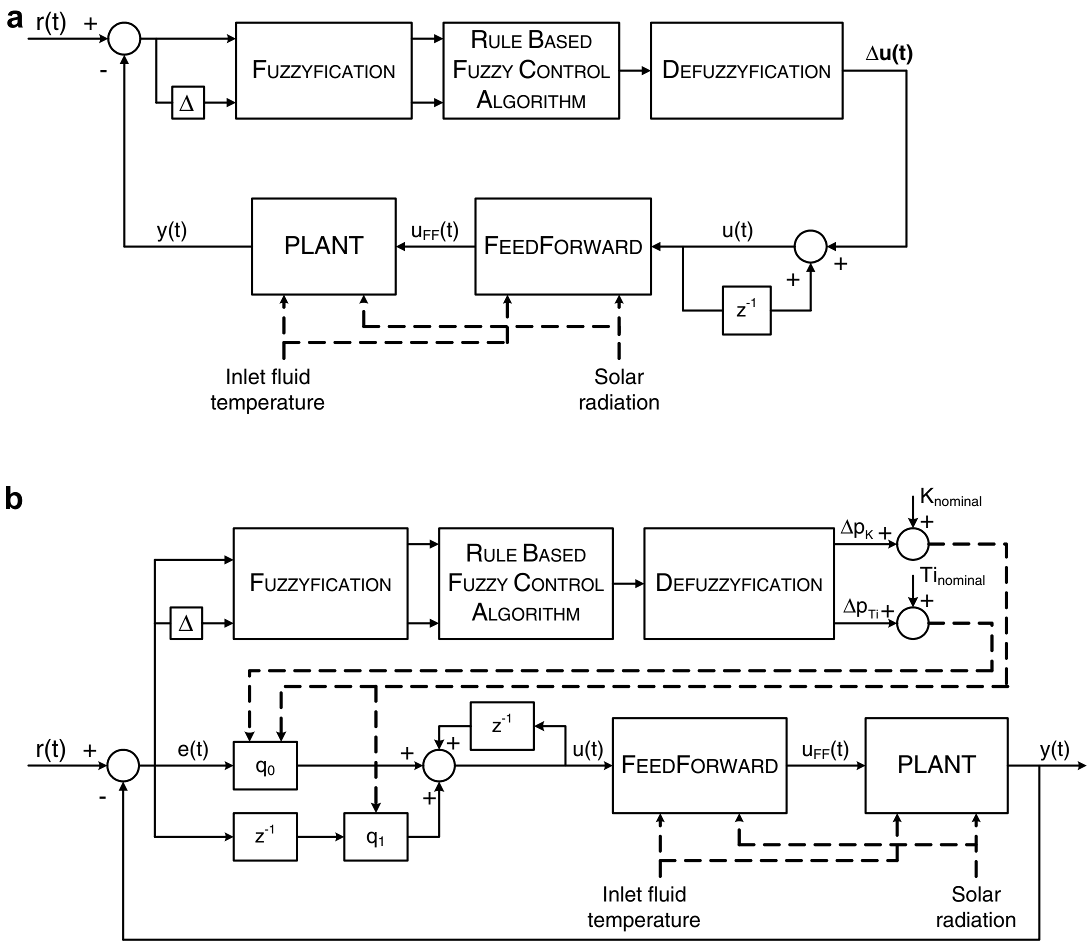

Fig. 8. Block diagrams of typical fuzzy logic controllers (FLC). (a) Direct fuzzy logic control, (b) incremental fuzzy PI control.

for the feedforward controller). The implementation of the controller was made by means of a fuzzy associative memory (FAM) whose centres were heuristically obtained. After this first application of FLC, the same idea was used in Luk et al. (1997) to obtain direct FLC and in Berenguel et al. (1997a) to obtain fuzzy logic based PID controllers, where the parameters of PID controllers where modified according with a fuzzy logic inference mechanism (Fig. 8b). Fig. 9 shows that very good results were obtained when implementing the scheme in Fig. 8a. In Gordillo et al. (1997), the application of genetic algorithms was firstly introduced to automatically tune the FLC developed by Rubio et al. (1995), by obtaining the centres of the FAM describing the controller using an optimization algorithm with intensive use of data obtained in closed-loop under manual and automatic operation. A comprehensive overview of these developments can be found in Camacho et al. (1997a), Berenguel et al. (1999) and Rubio et al. (2006). In Markou and Petropoulakis (1998), PID-type fuzzy controllers similar to that of Berenguel et al. (1997a) were used in series with a feedforward controller developed by Valenzuela and Balsa (1998) in order to maintain a reference temperature in the Acurex DCS. The controller was tuned and tested on a nonlinear computer model of the plant (Berenguel et al., 1994) and then tested on the actual plant. Ke et al. (1998) used a unique hierarchical genetic algorithm (HGA) for the design and optimization of a FLC similar to that developed by Rubio et al. (1995), minimizing the number of fuzzy membership functions and rules applied. HGA is used to optimize the fuzzy membership functions, while the fuzzy rules also proceeds an evolution process for the realization of a set of fuzzy rules that can be optimally obtained. In Luk et al. (1999), again genetic algorithms are used to develop a FLC which rule base encompasses an empirical set of ‘if-then’ rules. Stirrup et al. (2001) and Loebis (2000) developed a control scheme that employs a fuzzy PI controller, for the highly nonlinear part of the operating regime and gain scheduled control over the more linear part of the operating envelope. In order to satisfy performance characteristics for the plant at different points in the operating regime, a multiobjective genetic algorithm is used to design the parameters of the fuzzy controller. The resulting controller is shown to both satisfy the desired performance criteria and have a reduced number of terms compared with a conventional design approach. All these works use the feedforward controller and the simulator developed by Berenguel et al. (1994). For the linguistic equation approach presented in Juuso et al. (1997,

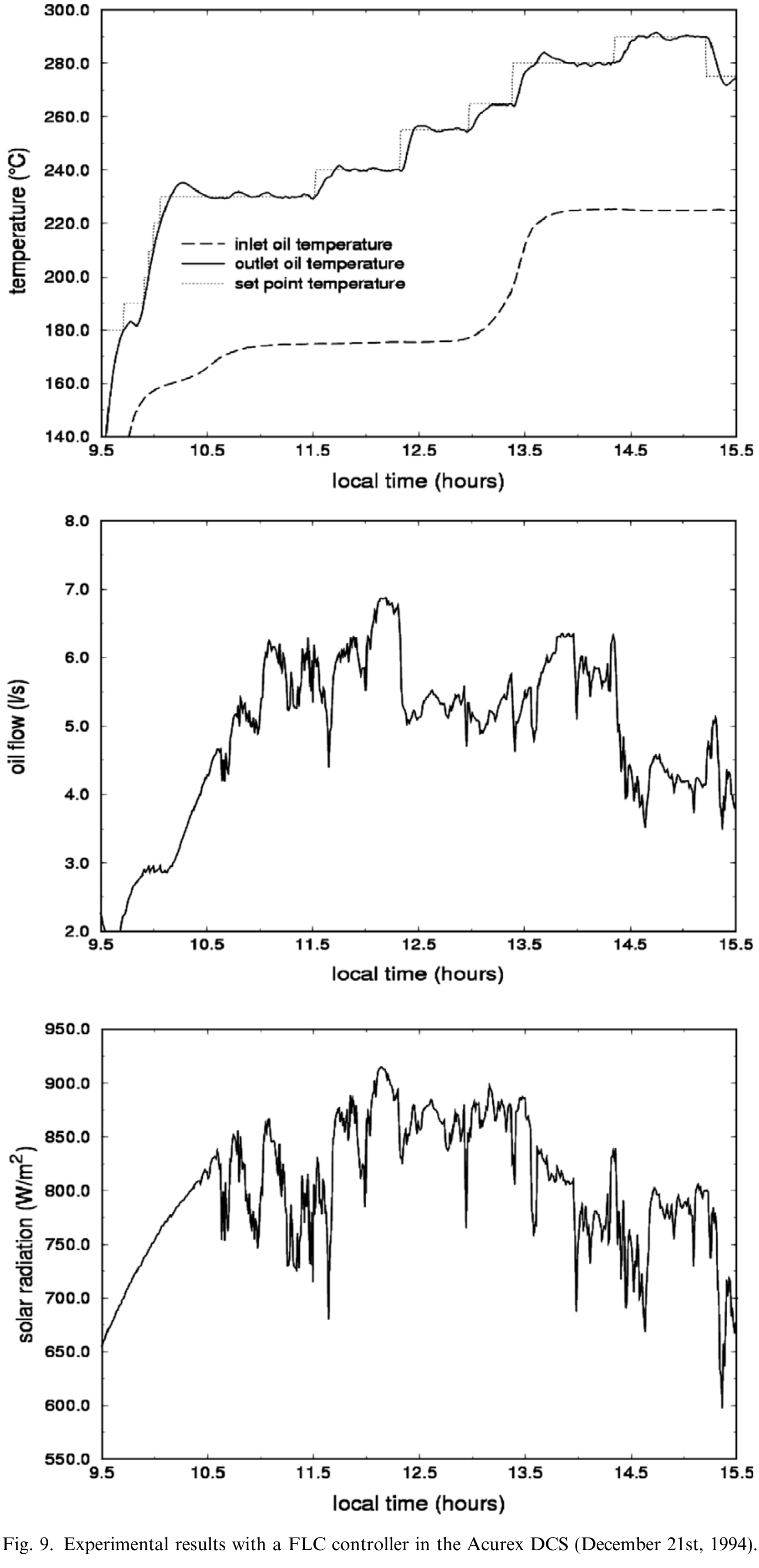

Fig. 9. Experimental results with a FLC controller in the Acurex DCS (December 21st, 1994).

1998a,b), Juuso (1999) and Oksanen and Juuso (1999), the fuzzy rules are replaced by linguistic equations. In fuzzy linguistic equations, fuzziness is taken into account by membership functions – linguistic equations approach does not necessarily need any uncertainty or fuzziness. Real valued linguistic equations provide a basis for a sophisticated nonlinear system where fuzzy set systems are used as a diagnostical tool. Fuzzification and defuzzification are integrated to the flexible generated for membership definitions. The linguistic equation controller applied in Juuso et al. (1997, 1998a,b), Juuso (1999) and Oksanen and Juuso (1999) is based on the PI-type fuzzy controller. Nonlinearities are introduced to the system by membership definitions that correspond to membership function used in FLC. This is the main difference to the FLC presented in Rubio et al. (1995), where the nonlinearities are handled through the rule base. Operation of the controller is modified by variables describing operating conditions (temperature difference between inlet and outlet temperatures and solar radiation); the implemented controller consists of a three level cascade controller. The linguistic equation controller reacts to variable irradiation conditions very efficiently since the control surface is changed only gradually. In Juuso and Valenzuela (2003), new results of the multilevel linguistic equation controller are shown. The controller combines smoothly various control strategies into a compact single controller. Control strategies ranging from smooth to fast are chosen by setting the working point of the controller. The controller takes care of the actual setpoints of the temperature. The operation is very robust in difficult conditions: startup and setpoint tracking are fast and accurate in variable radiation conditions. Cardoso et al. (1999) developed a fuzzy switching supervisor PID control approach using a feedforward compensator. The use of a supervisor is easy to implement because it needs very little knowledge about the process, can lead to a highly nonlinear control law, increasing the robustness of the control system and can provide a user interface for expressing precisely the specifications in terms of closed-loop performance. The supervisor was implemented using a Takagi–Sugeno fuzzy strategy, to implement an on-line switching between each PID controller, according to the real time measured conditions. The local PID controllers were previously tuned off-line, using an ANN approach that combines a dynamic recurrent nonlinear ANN model with a pole placement control design. The number of local controllers, to be employed by the supervisor, is reduced using the c-Means clustering technique. The feedforward controller proposed by Camacho et al. (1992) was used in parallel configuration. The same approach was used by Henriques et al. (1999a,b). In Pereira and Dourado (2002a,b), a neuro-fuzzy system based on a radial basis function (RBF) network and using support vector learning is considered for nonlinear modeling and applied to the output regulation problem. In Ghezelayagh and Lee (2002), the application of a neuro-fuzzy identification for predictive control is performed. The same idea is exploited in Jalili-Kharaajoo and Besharati (2003) and Jalili-Kharaajoo (2004), where an intelligent predictive controller is proposed. But in both cases, only simulation results are provided using the simulator in Berenguel et al. (1994). In Flores et al. (2005), a fuzzy predictive control scheme is developed. 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 MPC allowing the specification of more complex requirements.

12. Neural network controllers (NNC)

Some of the approaches to control DCS using NNC has been commented in the previous sections. Arahal et al. (1998b) and Berenguel et al. (1998) presented an application of ANN identification to obtain models of the free response of the solar plant to be used in the algorithm proposed by Camacho and Berenguel (1994b), see Fig. 10a. In Cardoso et al. (1999), the local PID controllers of a switching strategy were previously tuned off-line, using an ANN approach that combines a dynamic recurrent nonlinear ANN model with a pole placement control design (Fig. 10b). Gil et al. (2001) used recurrent ANN aimed at obtaining a pseudo-inverse of the plant to apply FLC techniques. Further improvements led to the works of Gil et al. (2002b), where a nonlinear adaptive constrained MPC scheme is presented using nonlinear state-space ANN and their online training. The identification of the ANN is performed in two levels. First, a parameterization is obtained for the selected topology by training the ANN on a batch mode, following an online estimation of weights in order to get rid of any model/plant mismatch due to the quality of the offline training set or the time variant nature of some plant's parameters. In Gil et al. (2003), another nonlinear adaptive constrained MPC scheme with steady-state offset compensation is developed and implemented. The ANN training is carried out online by means of a distribution approximation filter approach. In Gil et al. (2002a) and Henriques et al. (2002a), a NNC strategy is applied. The ANN is trained based on measured data from the plant providing a way of scheduling between a set of PID controllers, a priori tuned in different operating points by means of Takahashi rules. The scheduling variable is obtained from an ANN having as inputs the values of solar radiation, inlet oil temperature and reference (or outlet) temperatures. Thus, the scheduler implements an inverse of the plant at steady state. In Henriques et al. (2002b), the modeling capabilities of a recurrent ANN to replace the unknown system and the effectiveness and stability of the OR control theory (geometric approach) are combined, as it was commented in Section 9.

13. Other activities

Hierarchical multilayer control systems are also being recently developed (Cirre et al., 2004c, 2005b; Berenguel et al., 2005a) aimed at determining the optimal plant

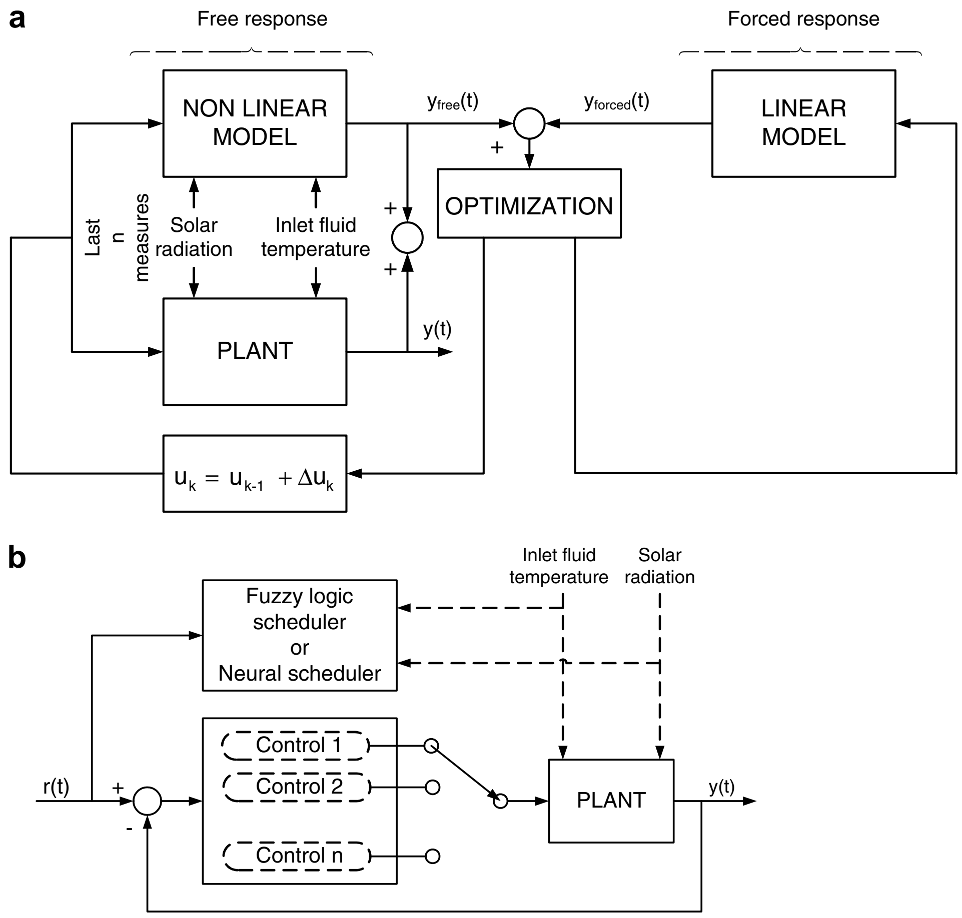

Fig. 10. Block diagrams of typical neural network controllers (NNC). (a) Neural network controllers, (b) neural/fuzzy switching control.

operating points automatically for maximizing the economic profit from selling the electricity produced.

The early detection of faults (system malfunctions) combined with a fault tolerant control strategy can help avoiding system shut-down, breakdown and even catastrophes involving human fatalities and material damage. The first trends in the application of this kind of techniques to DCS have been performed in two directions. On one hand, in Gil et al. (2003) the robustness of a constrained MPC was tested in the face of several faults on the actuator, sensors and system parameters. Further works (Cardoso et al., 2003, 2004) incorporate a fault diagnosis module and a supervisory system in order to detect, identify and accommodate these types of faults. On the other hand, related works are currently being performed within the scope of data-mining and monitoring techniques (Maciejewski et al., 2004, 2006; Berenguel et al., 2005b; Klempous et al., 2005), aimed at providing software tools helping to facilitate the operation and data exploitation and to predict possible failures in the system. These last works are based in the new generation of plants using water/steam as heat transfer fluid (Zarza et al., 2001, 2004; León and Valenzuela, 2002; León et al., 2002; Eck et al., 2003; Valenzuela et al., 2003, 2004), where PID controllers combined with feedforward controllers are extensively used (Valenzuela et al., 2004, 2005, 2006).

14. Concluding remarks

The main features of the different advanced control approaches used during the last 25 years to control distributed solar collector fields have been outlined and are summarized in Table 1. It is difficult to demonstrate the relative merits of one controller with respect to the others, since they are based on different conceptual and methodological approaches and the exact conditions in which the tests are performed are different (mainly in terms of solar radiation and inlet oil temperature conditions). As has been mentioned, the DCS may be described by a distributed parameter model of the temperature. It is widely recognized that the performance of PI and PID type controllers will be inferior to model based approaches (Camacho et al., 1997b; Meaburn and Hughes, 1995), taking into account that the plant is highly nonlinear as well as of infinite dimension (Johansen and Storaa, 2002a,b). Even when the plant is linearized about some operating point and approximated by a finite dimensional model, the frequency response contains antiresonance modes near

Table 1
Modeling and advanced control strategies

Reference	Controller													Comments
	PID	FF	MPC/ NMPC	AC	GS	CC	IMC	TDC	LQG	NC	RC	FLC	NNC	
Arahal et al. (1997, 1998a,b)			×										×	
Barão (2000) and Barão et al. (2002)				×						×				
Berenguel et al. (1994)		×												Modeling and simulation
Berenguel and Camacho (1995, 1996)				×			×							
Berenguel (1996)	×	×	×	×	×		×		×	×	×	×	×	Modeling and simulation
Berenguel et al. (1996)		×	×		×									
Berenguel et al. (1997a, 1999)	×	×										×		
Berenguel et al. (1997b, 1998)			×										×	
Berenguel et al. (2005a)														Hierarchical control
Berenguel et al. (2005b)														Data monitoring/ mining
Camacho et al. (1988)														Modeling
Camacho et al. (1992)	×	×		×										
Camacho and Berenguel (1993, 1994a)		×	×		×									
Camacho et al. (1994a)		×	×	×										
Camacho et al. (1994b)		×	×		×									
Camacho and Berenguel (1994b)		×	×		×					×				
Camacho et al. (1997a)		×										×		
Camacho and Berenguel (1997)		×	×	×							×			
Camacho et al. (1997b)	×	×	×	×	×		×		×	×	×	×	×	Modeling and simulation
Cardoso et al. (1999)	×	×										×		
Cardoso et al. (2003, 2004)			×	×									×	Fault tolerance
Carmona (1985) and Carmona et al. (1987)	×													Modeling and simulation
Carotenuto et al. (1985, 1986)										×				
Cirre et al. (2003)	×	×									QFT			
Cirre et al. (2004a,b)	×	×												Part I-optimization
Cirre et al. (2005a)										FL				
Cirre et al. (2004c, 2005b)														Hierarchical control
Coito et al. (1996, 1997)			×	×										
Farkas and Vajk (2002a,b)							×							
Flores et al. (2005)			×									×		
Ghezelayagh and Lee (2002)			×									×	×	
Gil et al. (2001)										FL			×	
Gil et al. (2002a)	×				×								×	
Gil et al. (2002b, 2003)			×	×									×	
Gordillo et al. (1997)		×										×		
Henriques et al. (1999a,b)	×											×	×	
Henriques et al. (2002a)	×				×								×	

Henriques et al. (2002b)									OR			×	
Igreja et al. (2003)				×					FL				
Ionescu et al. (2004)												×	Part I-modeling
Jalili-Kharaajoo and Besharati (2003) and Jalili-Kharaajoo (2004)			×								×	×	
Johansen et al. (2000)					×			×					
Johansen and Storaa (2002a,b)	×	×							×				
Juuso et al. (1997, 1998a,b) and Juuso (1999)											×		
Juuso and Valenzuela (2003)				×							×		
Ke et al. (1998)											×		
Klein et al. (1974)								×					
Klempous et al. (2005)													Data monitoring/ mining
Lemos et al. (2000)			×						×				
Loebis (2000) and Stirrup et al. (2001)		×									×		
Luk et al. (1997, 1999)		×									×		
Maciejewski et al. (2004, 2006)													Data monitoring/ mining
Markou and Petropoulakis (1998)	×										×		
Meaburn and Hughes (1993a,b)				×									Part I-modeling
Meaburn and Hughes (1994, 1995)				×	×								
Meaburn (1995)		×	×	×									
Meaburn and Hughes (1996)			×				×						
Meaburn and Hughes (1997)		×											
Nenciari and Mosca (1998)				×	×								
Normey-Rico et al. (1998)			×				×			×			
Oksanen and Juuso (1999)											×		
Orbach et al. (1981) and Rorres et al. (1980)								×					
Ortega et al. (1997)		×								H_∞			
Pereira and Dourado (2002a,b)											×	×	
Pérez de la Parte et al. (2007)										SMC			
Pickhardt (1998, 1999, 2000a)				×	×								
Pickhardt and Silva (1998)			×						×				
Pickhardt (2000b)				×	×								
Rato et al. (1997a)				×		×							
Rato et al. (1997b, 1998)				×	×								
Rubio (1985) and Rubio et al. (1986, 1989)	×			×									
Rubio et al. (1995)		×									×		
Rubio et al. (1996)								×					
Rubio et al. (2006)	×	×	×	×	×	×							
Sbarciog et al. (2004) and Wyns et al. (2004)												×	Part I-modeling
Silva et al. (1997)				×		×							
Silva et al. (1998)		×	×	×									
Silva (1999a)			×	×									
Silva (1999b,c) and Silva et al. (2002a,b,c)			×	×					×				
Silva et al. (2003a)			×						FL				

(*continued on next page*)

Table 1 (*continued*)

Reference	Controller													Comments
	PID	FF	MPC/ NMPC	AC	GS	CC	IMC	TDC	LQG	NC	RC	FLC	NNC	
Silva et al. (2003b)			×	×						×				
Stirrup et al. (2001)					×							×		
Stuetzle et al. (2004)		×												
Valenzuela and Balsa (1998)		×												
Valenzuela et al. (2003, 2004, 2005, 2006)	×	×				×								Part I-DSG
Vaz et al. (1998)	×				×									
Willigenburg et al. (2004a,b)									×					

the bandwidth that must be taken into consideration in the controller in order to achieve high performance (Meaburn and Hughes, 1993a). Thus, the "ideal" controller should be high-order and nonlinear. The control techniques outlined in this paper range from the simplest ones to others with high complexity, trying to find a trade-off between commissioning time and performance. Different characteristics have been studied and are the basis for the selection of each technique mainly depending on the knowledge the user has on the process and on the techniques: degree of difficulty in the obtaining of the model/controller tuning, degree of difficulty in the model/controller implementation, degree of acceptance by the operators, robustness, stability and performance results, use of design and/or implementation constraints, disturbance rejection capabilities, starting up of the operation and existence of real tests.

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