Abstract:
Distributed collector solar fields are spatially distributed engineering systems which aim at collecting and storing energy from solar radiation. They are formed by mirrors which concentrate direct incident sun light in a pipe where an oil able to accumulate thermic energy flows. From the control point of view, the objective consists of making the outlet oil temperature to track a reference signal by manipulating the oil flow, in the possible presence of fast disturbances caused by passing clouds. This paper reviews from a unified standpoint adaptive algorithms to solve this control problem. Besides their intrinsic interest, distributed collector solar fields are representative of a class of systems with technical interest, involving transport phenomena, to which the methods considered can be applied. A trade-off is shown to exist: By incorporating more information about plant dynamics, the control algorithms yield an increased performance, but they become less general.

Keywords:

1. INTRODUCTION.
Distributed collector solar fields are large, spatially distributed, engineering systems which aim at collecting and storing energy from solar radiation. Their interest is manifold. From a socio-economic point of view they answer a basic need of Society, viz. the need for clean and renewable sources of energy. From a scientific-technic perspective, they pose many challenging problems, in particular when their control is considered. Furthermore, the interest of the answers provided is not exhausted within the strict boundary of solar energy plants. Instead, the methods developed find application in a variety of plants, ranging from spray driers (Lemos et al., 2003) to highway traffic (Jeffrey, 2003), super-heated steam in boilers (Silva et al., 2000), plug-flow reactors (Shang et al., 2002) and population structure dynamics (Curtain et al., 1995). The above combined features motivate the study of advanced control methods for distributed collector solar
plants. As will be shown, when tackling such plants there is a significant level of uncertainty and hence the focus will be placed in adaptive methods.

1.1 Distributed collector solar fields

Fig. 1 shows the ACUREX field of Plataforma Solar de Almeria (PSA), located in the south of Spain, in which the experimental results presented hereafter have been obtained.

It is made up from mirrors which concentrate direct incident sun light in a pipe where an oil able to accumulate thermic energy flows. Fig. 2 shows a dismounted concentrating mirror. The field consists of 480 parabolic mirrors arranged in 20 East-West oriented rows, forming 10 parallel loops. The elevation of the mirrors is varied by a sun tracking controller.

The oil flowing in the pipe is an incompressible fluid, able to support temperatures up to 300°C. Since this oil is a very poor thermal conductor, heat diffusion effects in it may be neglected, a fact to be exploited in the plant model used for control design.

1.2 Control: State of the art

The above control problem may not adequately be solvable with a constant gain linear controller relying on a simple design. Fig. 6 (Barão, 2002) provides an example in which a constant gain PID controller tuned for higher values of the flow (low temperatures) yields unacceptable oscillatory responses in set-point changes. This motivated research on more sophisticated controllers of which (Barão, 2002; Berenguel...
The major role played by changes of solar radiation and plant uncertainty lead to the approach of (Camacho, 1992) where a pole placement self-tuning controller with a series feed-forward compensator is used. An improvement of the adaptation mechanism and of the underlying control law was possible by resorting to predictive adaptive control techniques. Different forms of adaptive GPC (Camacho, 1994a; Camacho et al., 1997a; Coito et al., 1997; Carotenuto et al., 1985; Carotenuto et al., 1986; Johansen et al., 2002; Lemos et al., 2000; Meaburn et al., 1994; Rubio et al., 1995; Rubio et al., 1996; Silva et al., 1997; Silva et al., 2003; Silva et al., 2003a) are significant examples. The monograph (Camacho, 1997) reviews in a comprehensive way some of these works.

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By making a frequency response analysis under conditions which correspond to linear behavior, it is possible to recognize the occurrence of anti-resonances (Meaburn et al., 1993). This is confirmed by a simplified analysis based on the PDE (partial differential equation) describing collector loop dynamics (Berenguel, 1995) and lead to the design of controllers based on frequency methods (Berenguel, 1995; Meaburn, 1994). In (Meaburn, 1994) a prescheduled adaptive controller for resonance cancellation has been presented and in (Berenguel, 1995) an adaptive control algorithm using an Internal Model Control structure together with a frequency design approach has been introduced.

While adaptive control already provides some form of accommodation of nonlinear behavior by adjusting the controller gains according to the operating point, explicit recognition of plant nonlinearities and their exploitation is much likely to lead to performance and robust stability improvements (i.e. the ability of the plant to meet control objectives in a wider set of operating conditions). First steps in this direction were made by employing gain scheduled constant parameter GPC (Camacho, 1994a) and switched multiple model supervisory controllers (Lemos, 2000).

In (Barão, 2002) a nonlinear controller is developed which explicitly takes into account the distributed parameter model of the solar plant. A nonlinear adaptive controller was designed using Lyapunov methods.

Also departing from the PDE (partial differential equation) model of the plant, (Johansen, 2002) proposes a design based on Lyapunov methods, using internal energy as Lyapunov function. Lyapunov methods, but using a quadratic function, are also the realm of (Carotenuto, 1985; Carotenuto, 1986).

Finally, (Silva, 2003; Silva, 2003a) provides a major advance by using a time varying sampling interval. This approach, to be discussed hereafter, implements a change in time scale which linearizes the plant, allowing very high sudden changes in reference.

1.3 Paper contributions and organization

The contribution of this paper consists in a review of methods for adaptive control of distributed collector solar fields. Whenever possible, this review takes as unifying standpoint a first principles model which reflects plant dominant dynamics. Two broad classes of control algorithms are considered: Data driven and model driven. As such, a trade-off is shown to exist: By incorporating more information about plant dynamics, an increased performance is yielded, but the algorithms become less general, in the sense of being more plant specific.

Apart from the introduction in which a typical distributed collector solar field is described and the state of the art for the control of this type of plants is reviewed, and the conclusions, the paper is divided in three main parts. The first concerns models and dynamics, the second concerns the black-box approach to control and the last addresses model driven methods.
A word of caution is due: While in the state of the art subsection an effort has been made to refer the most representative works throughout the world, the body of the paper is biased by the author’s interests and reflects its own experience.

2. MODELS AND DYNAMICS

In this section, a reduced complexity model is introduced and used to explain the dominant dynamics of the plant. This model is not adequate for simulation. For this purpose (Camacho et al., 1988; Camacho, 1997) provide suitably detailed models. The simplicity of the model considered here is however instrumental in control algorithm development in section 4, with the inaccuracies compensated by adaptation.

2.1 Physical models

Consider a single loop of the solar collector field. Given the small diameter of the pipe when compared to its length, and assuming incompressibility of the fluid and no diffusion, it is possible to model the temperature distribution along the pipe by a partial differential equation (PDE) of the form:

\[ \frac{\partial T(z,t)}{\partial t} + u(t) \frac{\partial T(z,t)}{\partial z} = \alpha R(t) \]  

where \( T(z,t) \) is the difference of oil temperature with respect to the inlet oil temperature (assumed constant), at each position \( z \) of the pipe and at time \( t \), \( u \) is the manipulated variable oil speed (proportional to oil-flow), \( R \) is the corrected solar radiation. In the above model heat losses to the environment are not considered. Furthermore, model (1) discards energy accumulation in the metal mass of the pipe, as well as the nonlinear thermodynamic characteristics of the oil. Hence, parameter \( \alpha \) depends not only on the mirror efficiency but also on the working point through these characteristics.

In order to obtain a lumped parameter approximation of (1), divide the pipe in \( n \) segments of length \( h \) such that \( z_i = ih \), \( L = nh \) is the pipe length and \( T_i = T(ih,t) \). Defining the state variables

\[ x_i(t) = T(ih,t) \quad i = 1, \ldots, n \]  

the process dynamics is thus approximately described by the system of nonlinear ODE’s:

\[ \dot{x}_i = -u \frac{1}{h} (x_i - x_{i-1}) + \alpha R, \quad i = 1, \ldots, n \]  

where the dot denotes derivative with respect to time \( t \) and \( x_0 = 0 \). Defining the state \( x = [x_1 \ldots x_n]^T \) and the vector fields

\[ f = \alpha R \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}, \quad g(x) = - \frac{1}{h} \begin{bmatrix} x_1 \\ x_2 - x_1 \\ \vdots \\ x_n - x_{n-1} \end{bmatrix} \]

Thus, an initial temperature distribution along the pipe will propagate in time along the characteristic lines as shown in fig. 7. The effect of radiation is to progressively increase the value of temperature. This may be shown by semigroup methods (Lemos, 2003) (which have the advantage of tackling more complicated equations, e.g. modelling diffusion effects) or by integrating (1) with the classical Laplace method for solving first order quasi-linear PDE’s. This yields a solution of (7) given by

\[ T(z,t) = T(z - \int_{t_0}^t u(\sigma) d\sigma) + \int_{t_0}^t R(\sigma) d\sigma \]  

3. CONTROL: BLACK-BOX APPROACH

This section is concerned with the black-box approach to control, in which the algorithms are data driven and no explicit use is made of a plant model obtained from first principles. As the name indicates, the plant is considered a "black-box", with their structure and distributed character ignored. Linear lumped parameter predictive models are identified from input/output data and adapted to compensate for nonlinearities and uncertainty. Since the controllers thereby obtained can be applied with a minimum of \emph{a priori} plant knowledge, they form an important base-line to which other methods may be compared.
3.1 Predictive adaptive control

Predictive adaptive control aim at minimizing in a receding horizon sense an extended horizon cost function on the basis of models estimated on-line from plant data. The algorithm selected is the MUSMAR controller (Silva, 2000; Coito, 1997). The MUSMAR controller is based on a number of separately estimated predictive models. In the presence of plant/model mismatches the redundancy thereby introduced proves important for achieving a correct control action. If the prediction horizon is high enough, in the neighborhood of a cost extremum, the controller gains will be updated in the direction close to the opposite of the gradient of the cost modified by the inverse of the Hessian matrix. As a result, it has been shown that the only possible convergence points of the algorithm are the local minima of the steady state quadratic cost constrained to the chosen controller structure. Extensive simulation results show that the algorithm is actually able to find these minima, even in the presence of unmodelled plant dynamics. The MUSMAR algorithm reads as follows:

At the beginning of each sampling interval \( t \) (discrete time), recursively perform the following steps:

1. Sample plant output, \( y(t) \) and compute the tracking error \( \hat{y}(t) \), with respect to the desired set-point \( y^*(t) \), by:
   \[
   \hat{y}(t) = y^*(t) - y(t)
   \]

2. Using Recursive Least Squares (RLS), update the estimates of the parameters \( \theta_j, \psi_j, \mu_{j-1} \) and \( \phi_{j-1} \) in the following set of predictive models:
   \[
   \hat{y}(t + j) = \theta_j u(t) + \psi_j s(t)
   \]
   \[
   u(t + j - 1) = \mu_{j-1} u(t) + \phi_{j-1} s(t)
   \]
   \( j = 1, \ldots, T_H \)

where \( \approx \) denotes equality in least squares sense and \( s(t) \) is a sufficient statistic for computing the control, hereafter referred as the pseudo-state, given by

\[
\begin{align*}
    s(t) &= [\hat{y}(t) \ldots \hat{y}(t-n_a+1) u(t-1) \ldots u(t-n_b) \\
          &\quad w_1(t) \ldots w_1(t-n_{a_1}) \ldots w_N(t) \ldots w_N(t-n_{a_N})]^T
\end{align*}
\]

where the \( w_i \) are samples of auxiliary variables such as intermediate process variables or accessible disturbances. Since, at time \( t \), \( \hat{y}(t+j) \) and \( u(t+j) \) are not available for \( j \geq 1 \), for the purpose of estimating the parameters, the variables in (8,9) are delayed in block of \( T_H \) samples.

3. Apply to the plant the control given by
   \[
   u(t) = F's(t) + \eta(t)
   \]
   where \( \eta \) is a white dither noise of small amplitude and \( f \) is the vector of controller gains, computed from the estimates of the predictive models by
   \[
   F = -\frac{1}{\alpha} \left( \sum_{j=1}^{T_H} \theta_j \psi_j + \rho \sum_{j=1}^{T_H-1} \mu_j \phi_j \right)
   \]

with the normalization factor \( \alpha \) given by
   \[
   \alpha = \sum_{j=1}^{T_H} \theta_j^2 + \rho (1 + \sum_{j=1}^{T_H-1} \mu_j^2)
   \]
   and \( \rho \geq 0 \) a penalty in the control effort. The choice of the variables and the number of their past samples entering \( s(t) \) defines the structure of the controller. The pseudo-state \( s(t) \) also includes samples of auxiliary variables, in this case inlet oil temperature and solar radiation. These terms induce a feedforward action which speeds up rejection of accessible disturbances. The value of the prediction horizon \( T_H \) should be large enough so that the gains are close approximations to steady-state (infinite horizon) LQ optimal gains. However, if \( T_H \) is too large, predictive model parameter estimates loose accuracy and this results in gain detuning and consequent loss of performance. A trade-off has thus also to be made for choosing \( T \).

Fig. 8 shows the results obtained with standard MUSMAR. The controller has been configured by choosing \( T_H = 15 \), \( \rho = 0.001 \), \( n_a = 3 \), \( n_b = 2 \) and also including in the pseudo-state the most recent sample of the reference, the solar radiation and the inlet oil temperature. Although a good tracking performance is achieved, there is an undesirable high frequency oscillation in the manipulated variable.

3.2 Dynamic weights

In order to cancel the high frequency oscillation which appears in the manipulated variable in fig. 7, one possibility is the use of dynamic weights (Coito, 1997). Corresponding results are seen in fig. 9. The high frequency oscillation is washed out. Nevertheless, there is still an oscillatory behavior of the manipulated variable and it is not safe to perform step changes of amplitude higher than 20°C.
Oil outlet temperature and reference \( T \) [°C]

3.3 The start-up problem

A crucial issue in adaptive control is start-up. If the algorithm is initialized with no plant information, e.g. by setting all the initial gains and parameters to zero and the RLS covariance matrix entries to high values, an initial strong transient may result before the controller "learns" plant dynamics (fig. 10). This nasty behavior can be avoided by initializing all parameter estimates, the gains and the entries of the covariance matrix in the RLS identifiers with values from a previous run. The adaptation transient is avoided using this technique in fig. 9. Another possibility is to resort to a dual version of MUSMAR (fig. 11) (Silva et al., 1998) where a bicriterial optimization approach is followed.

3.4 Cascade control

In a cascade control framework (Rato et al., 1997), the average of the temperatures at the outlet of the loops is taken as the intermediate variable \( T_{av} \) in fig. 12) and the main process variable is the temperature of the oil entering the storage tank, after a long passive pipe. In this way, the dynamics is decomposed in two parts: The dynamics of the collector loops, which relate the oil flow to \( T_{av} \); and the dynamics of the pipe connecting the outlet of the loops with the inlet of the storage tank, which relates the temperatures in both points \( T_{av} \) and \( T \). The former corresponds to the faster time constant (with a value of about 3 minutes). The latter corresponds to the slower time constant (in this case a pure delay of about 9 minutes in series with a time constant of about 2 minutes). It is remarked that the above values of the time constants are merely indicative since they vary according to the operating conditions, namely oil flow. The robustness features of MUSMAR with respect to uncertainty in plant i/o transport delay play a fundamental role here. Indeed, MUSMAR is equivalent to a bank of parallel self-tuners, each one tuned to a different value of plant delay and with different weights. If the actual plant delay is bigger than the delay assumed for a given self-tuning channel the corresponding weight will be automatically set to zero. Insensitivity to uncertainty in plant delay is thus achieved up to some degree. Clearly, the predictive horizon must be bigger than the plant i/o transport delay. The main disturbances enter the system through the field and correspond to the variations in solar radiation and loop inlet oil temperature. The disturbances entering through the pipe correspond to losses in the pipe. In case a cascade structure would not be used in controlling the temperature at the inlet to the storage tank, the long delay in pipe dynamics would lead to a poor tuning for disturbance rejection. With cascade control, the problems of rejecting disturbances in both subsystems are split apart.

Fig. 13 shows results obtained with adaptive cascade control. The curves are labelled as 1 (reference \( T^* \)), 2 (temperature \( T \) at the inlet of the tank), 3 (average temperature \( T_{ave} \) at the average of the outlet of the collector loops) and 4 (reference \( T_{ee} \), which is the variable manipulated by the outer loop).
3.5 Switched multiple model control

In switched multiple model control, linear models, referred as local models, are associated to sets of operating regimes, defined by process variables (oil flow, temperature, radiation) or conditions (normal, faulty). To each model a local controller is associated. Of this bank of controllers, the control actually applied to the plant is selected according to the principles that “the best model performance corresponds to the best controller performance” (which may not be true in the presence of unmodelled plant dynamics).

Fig. 14 shows a block diagram of the switched multiple model control system tested in the ACUREX field (Lemos, 2000). Here, $\delta u$ denotes increments of $u$, $y^*$ denotes the reference to be tracked by $y$, $k_\sigma(q)$ denotes the transfer function of the $\sigma$-th controller and $q$ denotes the forward shift operator. An integrator has been included in the loop, in series with the controller, in order to ensure zero steady-state position error. When the plant operating condition changes, the index $\sigma$ of the active controller, $k_\sigma(q)$, should be adjusted in order to match the operating conditions. This adjustment is performed by the supervisor. The supervisor consists of three stages: i) A shared-state estimator, $\Sigma_S$; ii) A performance weight generator, $\Sigma_W$; iii) A switching logic scheme, $\Sigma_S$.

Local models are 1-step ahead linear predictors of the output for the situation in which the plant is working in the $p$-th operating regime. The shared-state estimator generates a vector $\hat{X}_E$ to be used by a bank of models, each corresponding to one operating point. The performance weight generator computes a low pass filtering of the squared estimator errors. The switching logic scheme used consists in choosing the controller corresponding to the local model with the lowest performance signal, and assuring a minimum period of time between each switch. This period of time is referred as the dwell time and has been settled as 10 samples in the solar collector field example below.

Fig. 15 shows experimental results obtained with multiple model control. Just after 14, 3 h a strong and fast disturbance in solar radiation occurred, followed by a step change in the reference.

4. CONTROL: MODEL DRIVEN APPROACH

Although the black-box approach could yield algorithms which successfully control the plant, there are still undesirable performance limitations. In particular, when using the MUSMAR algorithm, there is still an undesirable ripple in the manipulated variable. Furthermore reference step changes higher then $20^\circ C$ lead to excessive overshoot or to a sluggish response.

In order to overcome these drawbacks, model driven algorithms are now considered.

4.1 Exact feedback linearization

Input-output exact linearization consists on finding a state transformation $z = \Phi(x)$ and input transformation $u = u(v)$ where $v$ is the transformed input, such that the transformed system has the form of a
series of $r$ integrators in series connecting $v$ to $y$ plus some internal dynamics, where $y = h(x)$ is the system output and $r$ is the so called relative degree.

Consider the system defined by (3) with the output defined by

$$y = h(x) = x_n$$

(14)

In this case (Barão, 2002) the relative degree is $r = 1$ and the linearizing control law is given by

$$u = \frac{-L_f h(x) + v}{L_g h(x)} = \frac{\alpha R - v}{x_n - x_{n-1}} h$$

(15)

Eq. (15) provides a transformation such that, from the transformed input $v$ to the output $y$, the dynamics reduces to a pure integrator. Once $v$ is found with an appropriate control law, the actual control $u$ to apply to the plant is computed from $v$ by (15). It is remarked that this computation requires the values of the states $x_n$ and $x_{n-1}$ which must be available for measurement. The measure of $x_{n-1}$ is not available in the plant considered for values of $n > 1$. In general, one possibility would be to estimate this variable. Another line of work consists in using approximate models.

Fig. 16 shows the results obtained on the ACUREX field with exact feedback linearization when $x_{n-1}$ is replaced in (15) by $x_0$. With the above control strategy it remains to show that the internal dynamics is stable. For the solar collector plant at hand, a convenient way for studying internal dynamics is by considering tracking dynamics. This corresponds to the internal dynamics when the output is perfectly tracking the reference. Fig. 17 shows an example of internal tracking dynamics.

4.2 Lyapunov adaptation

Control is now designed on the basis of the simplified model:

$$\dot{y} = -u(y - y_0) \frac{1}{L} + \alpha R$$

(16)

where $y$ is the outlet oil temperature, $y_0$ is the inlet oil temperature and $u$ is the oil flow velocity. The resulting equations may be interpreted by taking $n = 1$.

In (16) the optical efficiency $\alpha$ is not exactly known in advance and, furthermore, it includes modelling errors, being expected to change slowly. It is thus to be estimated. Let $\hat{\alpha}$ denote the true optical efficiency, $\hat{\alpha}$ an estimate of $\alpha$ and $\tilde{\alpha}$ the difference between the two. The actual control signal applied to the plant is given by

$$u = \frac{\hat{\alpha} R - v}{y - y_0} L$$

(17)

and the linearised system is

$$\dot{y} = v + \tilde{\alpha} R$$

(18)

In order to obtain an adaptation law for updating $\hat{\alpha}$, an argument based on the Lyapunov’s Direct Method is used. For that sake, consider the candidate Lyapunov function defined by

$$V(e, \hat{\alpha}) = \frac{1}{2} e^2 + \frac{1}{\gamma} \tilde{\alpha}^2$$

(19)

where $\gamma > 0$ is a constant parameter and $e$ is the tracking error defined by

$$e(t) = y_r - y(t)$$

(20)

$y_r$ being a constant set-point. Since the linearised system is an integrator, there is no need to include integral action in the controller. Thus, let the control in continuous time be given by the PD law

$$v = k_p e - k_d \dot{y}$$

(21)

with $k_p$ and $k_d$ constant gains. For $V$ to be a Lyapunov function, the following adaptation law has to be used:

$$\dot{\hat{\alpha}} = -\frac{\gamma}{1 + k_d} Re$$

(22)

With this choice, $\dot{V}$ is negative semidefinite if $k_p > 0$ and $k_d > -1$. Furthermore, by LaSalle’s invariance theorem, all the trajectories converge to the maximum invariant set where $\dot{V} = 0$, implying that

$$\lim_{t \to \infty} y(t) = y_r$$

(23)

Fig. 17 shows results obtained with exact feedback linearization and Lyapunov adaptation (Barão, 2002).
4.3 Time varying sampling

Another possibility to linearize (1) is by considering a change in time scale given by
\[ \frac{d\tau}{dt} = u(t) \]  
and the new manipulated variable
\[ v(\tau) = \frac{R(t)}{u(t)} \bigg|_{t=\varphi(\tau)} \]  

In the "warped" time scale \( \tau \) the characteristic curves become straight lines and equally spaced samples in space correspond to equally space samples in time (fig. 19) and the product between the manipulated variable and the state disappears. The new time scale \( \tau \) is implemented by using a time varying sampling (Silva, 2003; Silva, 2003a). Fig. 20 shows a step of 40\(^\circ\)C with very small overshoot.

4.4 Dynamic motion planning

The use of time varying sampling allows the solution of the dynamic motion planning problem using flat system methods. An example of transfer between two stationary states is shown in fig. 20.

5. DISCUSSION AND CONCLUSIONS

This paper provides a comprehensive overview of algorithms for adaptive control of distributed collector solar systems. The controllers are grouped in two main classes: Data driven and model driven. Data driven controllers can be applied to different plants but they have performance limitations. Model driven controllers explore the dominant dynamics of the plant thereby yielding higher performance but they are more plant specific. An important idea is the use of time varying sampling.

6. REFERENCES


