ADAPTIVE PREDICTIVE AND SWITCHING CONTROL OF A DISTRIBUTED COLLECTOR SOLAR FIELD

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Abstract: This paper reports experimental research work on the application of adaptive predictive and switching control algorithms to a distributed solar collector field. For adaptive predictive control a number of strategies are considered, including adaptive predictive control with dynamic weights, cascade control and dual control. The emphasis is put on the adaptation of the control algoritms to cope with the changes in the dynamic behavior of solar power plant.

Keywords: Predictive control, adaptive control, switching control, solar energy.

1 INTRODUCTION

This paper reports research work on adaptive predictive and switching control algorithms for a distributed solar collector field. The emphasis is put on the adaptation of the control algoritms to changes in the dynamic behavior of solar power plant. These changes are caused not only by the change in the operating point, but also by the time varying characteristics of the plant.

The field used in these experiments is described in available literature [6, 7]. The field consists of parabolic mirrors arranged in East-West oriented rows, forming 10 parallel loops. The parabolic mirrors concentrate the radiation in a steel pipe thus heating a synthetic oil which flows inside. This oil is pumped from the bottom of the storage tank through the field till the top of the tank.

The main control objective is to keep the outlet temperature of the field at a specified value. To attain this purpose the oil flow is manipulated by the controller. The process to be controlled is characterized by the following aspects:

- Time varying input/output transport delay, since the delay effect depends on the manipulated variable (oil flow).
- Strong unmodelled dynamics considering a concentrated parameter model, since the plant would be best modelled by a distributed parameter system [7].
- Anti-resonant modes in the frequency response, which change with the incident radiation.
- Nonlinear behavior.
- The solar radiation, and the inlet field temperature act as fast disturbances with respect to the process dominant time constant.

These aspects call for control algorithms that cope with high levels of uncertainty as well as with fast changes in the dynamic behavior of the plant.

In section 2 the MUSMAR predictive adaptive algorithm is presented. The MUSMAR controller has been shown to have robustness characteristics with respect to unmodelled dynamics. Dynamic weights are also applied, in the cost functional, to reduce the oscilations in the closed loop step response. The MUSMAR controller is also used in a cascade structure to control the temperature at the input of the storage tank as shown in section 3. In section 4 a MUSMAR dual controller is described, and the startup smothing effect is ilustrated with experimental results. In section 5, a MUSMAR based switching algorithm is shown. In this switching control scheme the adaptation is attained choosing a controller from a finite set of

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fixed controllers sharing a common state. Some final conclusions are addressed in the section 6.

2 MUSMAR ALGORITHM

Consider a SISO ARMAX plant

$$A(q)y(t) = B(q)u(t) + C(q)e(t) \tag{1}$$

where $u(t)$ is the input; $y(t)$ is the output; $\{e(t)\}$ is a stationary zero-mean white sequence with variance σ_e^2. A, B, C are polynomials in the unit forward shift operator, q. Associated with (1) consider a quadratic cost functional

$$J_t^c = E\left\{ \frac{1}{T} \sum_{i=1}^{T} y^2(t+i) + \rho u^2(t+i-1) | \mathcal{O}^t \right\} \tag{2}$$

where $E\{.|\mathcal{O}^t\}$ stands for the mean conditioned on the information available up to time t, and a set of $2T$ predictive models

$$\begin{gathered} \hat{y}(t+i) = \hat{\theta}_i u(t) + \hat{\psi}_i' s(t) \\ \hat{u}(t+i-1) = \hat{\mu}_{i-1} u(t) + \hat{\phi}_{i-1}' s(t) \\ i = 1...T \end{gathered} \tag{3}$$

where $s(t)$, called the pseudostate, includes past values of the input and output,

$$\begin{aligned} s(t) = [&y(t)\ y(t-1)\ ...\ y(t-n+1) \\ &u(t-1)\ u(t-2) ... u(t-m)]' \end{aligned} \tag{4}$$

and $\hat{\theta}_i$, $\hat{\psi}_i$, $\hat{\mu}_{i-1}$, $\hat{\phi}_{i-1}$ are recursive least squares (RLS) estimates of the real unknown parameters.

Upon use of the predictive models (3), the minimization of the cost functional (2) leads to

$$u_c(t) = F' s(t) \tag{5}$$

$$F = -\frac{\sum_{i=1}^{T} \hat{\theta}_i \hat{\psi}_i' + \rho \sum_{i=1}^{T} \hat{\mu}_{i-1} \hat{\phi}_{i-1}'}{\sum_{i=1}^{T} \hat{\theta}_i^2 + \rho \sum_{i=1}^{T} \hat{\mu}_{i-1}^2} \tag{6}$$

This strategy can be adaptively implemented as follows[8]:

1. Compute the recursive-least-square (RLS) estimate of the parameters θ_i, ψ_i, μ_i and ψ_i in the predictive models (3)
2. Update the feedback gains according to (5)
3. Calculate the control signal by

$$u(t) = F' s(t) + \eta(t) \tag{7}$$

where $\eta(t)$ is a white noise dither signal injected in order to fulfill a persistency of excitation condition and $s(t)$ is the pseudostate.

A detail of a step response obtained with the average collector loop outlet oil temperature is shown in fig. 1.

In this experiment, the sampling time is $15\,s$, $T = 15$, $n = 3$, $m = 2$, $\rho = 0.001$, and the variance of the dither noise $\sigma = 0.01$.

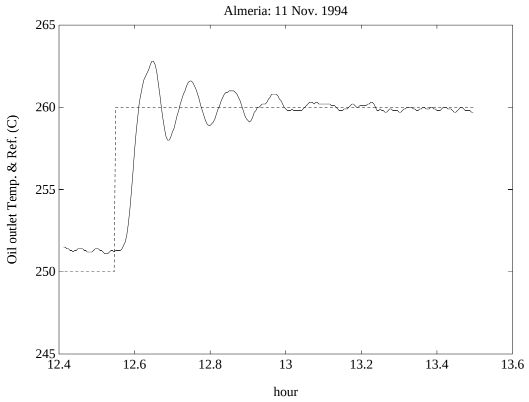

Figure 1: Reference and outlet temperature. Experiment performed on 11 November 1994

Dynamic weights

The cost functional (2) can be modified, introducing dynamic weights. Consider the modified cost functional

$$J_t^c = E\left\{ \frac{1}{T} \sum_{i=1}^{T} y_H^2(t+i) + \rho u_H^2(t+i-1) | \mathcal{O}^t \right\} \tag{8}$$

Where u_H is the filtered manipulated variable

$$u_H \triangleq H_u u \tag{9}$$

and $y_H(.)$ is the filtered plant output.

$$y_H \triangleq H_y\, y \tag{10}$$

$$H(q) = \frac{q-(1-\epsilon)}{\epsilon q} \tag{11}$$

where $0 < \epsilon < 1$ is a parameter that settles the velocity of response and q is the forward shift operator. This modified cost functional is equiva-

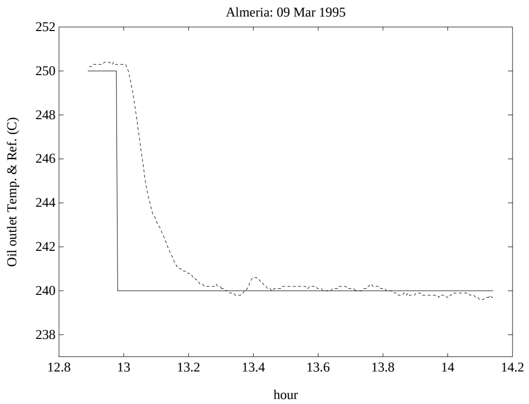

Figure 2: Reference and outlet temperature, MUSMAR controller with dynamic weights. Experiment performed on 9 March 1995

lent to the standard MUSMAR with the inclusion of filters in the manipulated variable $u(t)$ and the controlled variable $y(t)$. It can also be shown to be equivalent to the inclusion of an observer polynomial.

In fig. 2 the smothing effect of the filters in a step response can be observed. This experiment was performed with $\epsilon = 0.05$.

3 CASCADE CONTROL

Cascade control is a classical structure in process control. It explores the situation in which the system to be controlled can be split in two series subsystems P_1 and P_2 (fig.3) with the dominant time constant of P_1 being much faster than the dominant time constant of P_2. The two controllers

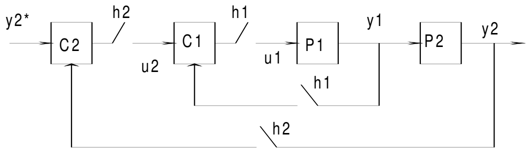

Figure 3: Multirate cascade control structure.

C_1 and C_2 are connected such that the manipulated variable of C_2, u_2, is the setpoint of C_1, thus forming two nested loops. Further, in a computer control framework, again exploring the difference between the dominant poles of P_1 and P_2, these subsystems are sampled at different rates h_1 and h_2, with

$$h_2 > h_1$$

The controlled variable, y_1, of the inner subsytem is the outlet field temperature and the controlled variable, y_2, of the outter subsytem is the oil temperature at the input of the storage tank. Roughly, the dynamic of the outter system, P_2,

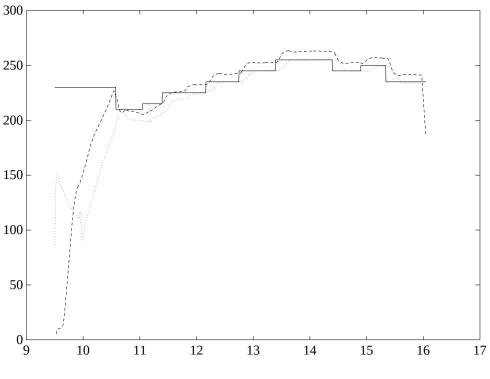

Figure 4: The reference to follow (solid), the average temperature at the outlet of the collector loops (dashed) and the temperature at the inlet to the storage tank (dotted). Experiment performed on 12 February 1996.

can be described as a time varying transport delay plus real poles.

The MUSMAR controller was employed in both loops of the cascade and a singular perturbation analysis has been performed in [3] stating conditions which characterize the possible convergence points.

Experimental results performed in the field can be observed in fig. 4, and 5. This experiment was performed with sampling times of 15 and 60 seconds, for the innner and the outer loops. For booth loops $n = 3$, $m = 2$, and $\rho = 0.001$.

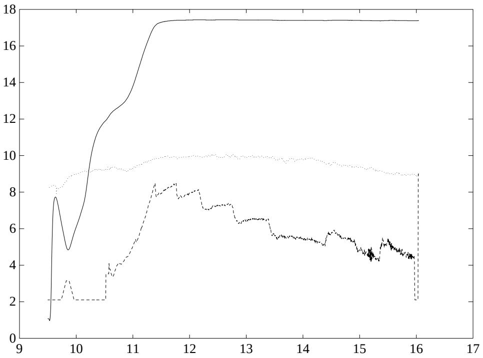

Figure 5: Field inlet temperature divided by 10 (solid), oil flow (dashed) and radiation divided by 100 (dotted). Experiment performed on 12 February 1996.

4 DUAL CONTROL

A dual version of the multipredictive adaptive regulator MUSMAR has been designed using a bicriterial optimization [4]. In the new version of the adaptive controller the uncertainty concerning the estimations of the controller parameters (covariance matrix of the estimation error) have been taken into account explicitly in the minimization of the control criteria (2), which yields the following cautious control law[4]

$$u_c(t) = -\frac{\sum_{i=1}^{T} \hat{\theta}_i \hat{\psi}_i' + \rho \sum_{i=1}^{T} \hat{\mu}_{i-1} \hat{\phi}_{i-1}' + \beta p_{us}'}{\sum_{i=1}^{T} \hat{\theta}_i^2 + \rho \sum_{i=1}^{T} \hat{\mu}_{i-1}^2 + \beta p_{uu}} s(t) \tag{12}$$

with $\beta = \sum_{i=1}^{T} \sigma_{yi}^2 + \rho \sigma_{ui}^2$, and p_{uu}, p_{us} are entries of the RLS covariance matrix. If β is made equal to zero, equation (12) reduces to the standard MUSMAR algorithm.

Instead of using constant power white dither noise added to the control input, in this new dual version, a second criteria is used for acceleration of the parameter estimation process by maximizing the predictive errors value. The criteria is given by

$$J_t^a = -E\left\{\frac{1}{T}\sum_{i=1}^{T}\left[y(t+i)-\hat{y}(t+i)\right]^2 + \alpha\left[u(t+i-1)-\hat{u}(t+i-1)\right]^2 |\mathcal{O}^t\right\};\quad \alpha>0 \tag{13}$$

yielding the following control signal

$$u(t) = u_c(t) + \vartheta(t)\,\mathrm{sign}\left\{p_{uu}u_c(t) + p'_{us}s(t)\right\} \tag{14}$$

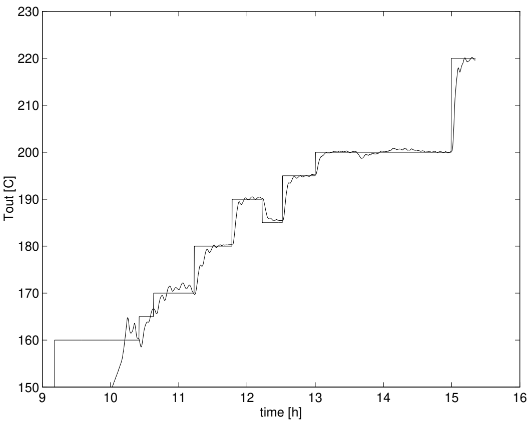

Figure 6: Reference and output temperature. Experiment performed on 16 July 1997.

Experimental results show that the algorithm provides a smoother start-up transient compared with the standard MUSMAR.

In fig. 6 and 7 it can be observed the result of an experiment with zero initial gains.

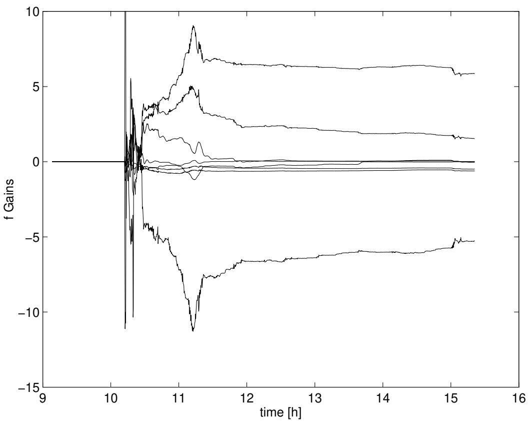

Figure 7: Controller gains. Experiment performed on 16 July 1997.

5 SWITCHING CONTROL

The classical adaptive schemes do not cope easily with strong and fast changes in the dynamic behavior unless the adaptation rate is made very high. This is not always possible. Thus, if there is some *a priori* knowlege about the plant dynamical behavior a switching control scheme may be applied [5].

The switching control algorithm here presented chooses a controller from a finite set of fixed controllers. The choice of the controller is made by a supervisor (fig.8) following the structure proposed in [10]. It consists of a shared-state estimator, Σ_E, a performance weight generator, Σ_W and a dwell time switching logic scheme, Σ_S.

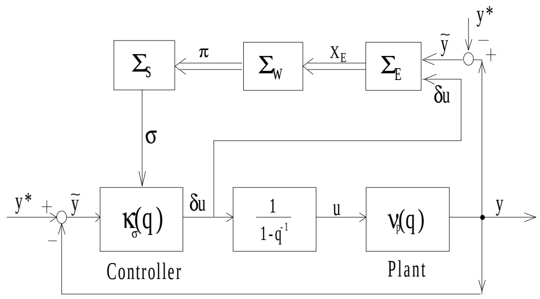

Figure 8: Switching control structure, with the supervisor and the integrator in the feedback control loop.

The shared-state estimator is an efficient way to implement a multi-estimator. A correct choice of the estimator state, X_E leads to MUSMAR-like pseudostate.

$$X_E(t) = [\delta u(t-1)\ s(t-1)]' \tag{15}$$

$$s(t) = [\tilde{y}(t)\ \tilde{y}(t-1)\ \ldots\ \tilde{y}(t-n+1)\ \ \delta u(t-1)\ \delta u(t-2)\ldots\delta u(t-m)]' \tag{16}$$

where $X_E(t)$ is the shared-state of the estimator, and $s(t)$ is the MUSMAR pseudostate.

As it is shown in fig. 8 an integrator has been included in the control loop in order to deal with steady state error.

The supervisor elects the active controller by choosing the one corresponding to the predictive model which best fits the plant model. Filtered squared estimator errors are used as performance signals,

$$\pi_i(t+1) = \pi_i(t)\lambda + (\hat{\tilde{y}}_i - \tilde{y})^2 \tag{17}$$

where $0<\lambda<1$ and π_i is the performance signal associated to the i-th nominal process model. In this paper a $\lambda = 0.9$ is used.

The set of controllers was determined running the MUSMAR algorithm with a plant model in different operating conditions, with constant radiation and inlet temperature and recording the gains thus yielded at convergence. The controller is defined by the MUSMAR gain vectors after convergence.

The adaptive MUSMAR algorithm used to generate the fixed controllers had the following parameters: sampling time is $30\,s$, $T = 10$, $n = 3$, $m = 2$, $\rho = 10-100$, and the variance of the dither noise $\sigma = 0.01$.

Figs. 9 and 10 provide an example of using switching control in the solar field, with a bank of 7 controllers.

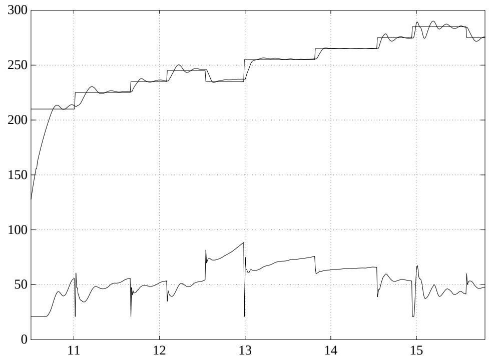

Figure 9: Reference, output, and $flow \times 10$. Experiment performed on 11 July 1996

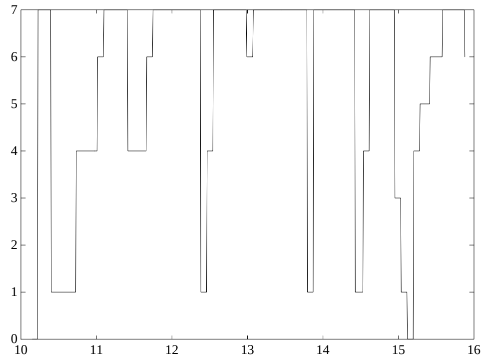

Figure 10: Supervisor output, σ. Experiment performed on 11 July 1996

6 CONCLUSION

A brief overall review of several strategies for the adaptive control of a distributed collector field has been made. The main points which have been successfully explored are the use of: Extented horizon predictive control to deal with uncertaint plant i/o transport delay; Redundant models to deal with unmodelled dynamics; Cascade control to deal with different time constants; Dual control to deal with startup transients; Switching control to deal with fast dynamic changes. The experience gained applying these ideas to the solar field has been very usefull in developing advanced control strategies for other plants with similar structures.

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