Control Strategies for Disturbance Rejection in a Solar Furnace

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Abstract: This paper addresses the temperature control problem in a solar furnace. In particular, two control strategies for the rejection of disturbances (represented by the variation of the input energy provided by the Sun, mainly because of passing clouds) are proposed. The first one is based on Generalised Predictive Control, where a nonlinear model is employed for free response prediction while a linearised model is used for the computation of the forced response. The second one is a constrained control strategy where the process input and output constraints are taken into account explicitly. In both cases an adaptation of the most significant process parameter is performed. Simulation results show the effectiveness of the methodologies.

Keywords: Solar furnace, disturbance rejection, predictive control, constrained control.

1. INTRODUCTION

In the last forty years there has been an increasing interest in solar energy because it represents a green and cheap source of energy. In this context, the material treatment in solar furnaces is one of the most promising applications that have been addressed. A solar furnace allows using solar energy for material treat consists of a collector system with tracking (usually made of flat-faceted heliostat) and a static parabolic system which concentrates a high percentage of the solar energy in its focal spot (Figure 1). In the process considered in this paper (see Section 2) the incoming light (that is, the energy flux entering the furnace) is regulated by means of a computer controlled louvered shutter (Berenguel et al., 1999). This type of testing in a solar furnace usually aims at improving the mechanical properties, such as hardness and wear resistance by means of heating the studied samples under varied temperature patterns. The application considered in this paper is the copper sintering, where a sample is exposed to long high temperature set points (near the melting point), so that small particles bond together and the aggregate shrinks resulting in a decrease of surface area and energy, which allows for ulterior study on a number of topics, e.g., volume diffusion of atoms (?). Due to the complexity and diversity of sample materials and temperature trends such research plants are usually manually controlled by expert operators. Obviously, the efficiency of the operations depends on the operators’ skill and therefore the presence of a properly designed automatic control system would have the advantage of providing adequate results for different operating conditions. For this reason, different control strategies have been published in literature (see, for example, (Lacasa et al., 2006; Berenguel et al., 1999; da Costa and Lemos, 2009)). However, the compensation of disturbances can be improved. Indeed, the input energy provided by the sun is variable, because of its daily cycle and because of passing clouds, which represent the most critical issue. This might obviously seriously decrease the performance of an experiment.

In this paper two different control strategies for the compensation of disturbances are presented. In both cases the input signal of the process is the aperture of the shutter and the output signal is the temperature measured by a thermocouple welded to the side or the back of the sample. The first method is based on Generalised Predictive Control (GPC) (Camacho and Bordons, 2004) while the second is a constrained control strategy based on a nonlinear control law which takes into account the input and output constraints of the plant. Model predictive control schemes based on linearized nonlinear models have been extensively used (Qin and Badgwell, 2003), but in this paper different approaches are developed. The obtained performance in both cases is compared with that obtained by a standard Proportional-Integral (PI) control.

The paper is organised as follows. In Section 2 the solar furnace is briefly described. In Section 3 the GPC-based control system is presented while in Section 4 the con-
trained control strategy is proposed. Simulation results (including the comparison with PI control) are shown in Section 5 while conclusions are drawn in Section 6.

2. DESCRIPTION OF THE SYSTEM

The process considered in this paper is the solar furnace (Martínez, 1996) of CIEMAT-Plataforma Solar de Almería (PSA, www.psa.es), which is the largest European center for research, development and testing of concentrating solar technologies located in Tabernas, Almería, South-East Spain. The solar furnace mainly consists of a heliostat which tracks the sun using an azimuth and pitch positioning mechanism and that reflects sunlight onto a concentrator disk. The amount of incoming energy is modulated using a louvred shutter (control actuator). The concentrator convex mirror gathers most of incoming sunlight from the outdoor heliostat onto a focal spot of 22 cm diameter, located inside a vacuum chamber where samples are placed for thermal tests. Figure 1 shows a representation of the plant layout.

![Solar furnace layout](image)

**Fig. 1.** PSA Solar furnace layout

The sample’s temperature model is described in (Berenguel et al., 1999). The model consists of the following first-order nonlinear equation (1):

\[
\rho_b \rho_c \frac{S_c}{S_f(90\%)} I S \alpha_0 \left[ 1 - \frac{\sin \left[ \alpha_0 \left( 1 - U/100 \right) \right]}{\sin \alpha_0} \right] - \alpha_c S_a \left( T^4 - T_e^4 \right) - \alpha_c S_a \left( T - T_e \right) = \frac{d(mC_e T)}{dt}
\]

where: \( \rho_b \) and \( \rho_c \) are the reflectivity coefficients of the heliostat and the concentrator [-]; \( S_c \), \( S_a \) and \( S_f(90\%) \) are the surfaces of the concentrator, of the sample and the focus area where the 90% of the solar input energy is concentrated [m²]; \( I \) is the input solar radiation [Wm⁻²], which is measured by using a pirheliometer; \( \alpha_0 \) is the absorption capacity of the sample [-]; \( \alpha_c \) is the emissivity of the sample [Wm⁻²K⁻¹]; \( \alpha_e \) is the capacity of the sample to exchange heat with the air [-]; \( \sigma \) is the Stephan-Boltzmann constant \( 5.67 \cdot 10^{-8} \text{Wm}^{-2}\text{K}^{-4} \); \( C_e \) is the specific heat \( [\text{Jkg}^{-1}\text{K}^{-1}] \); \( m \) is the sample mass [kg]; \( \alpha_0 \) is the maximum angular aperture of the shutter [rad]; \( T \) is the sample temperature [K] and suppose uniform into the body; \( T_e \) is the environmental temperature [K]; \( U \) is the angular percentage aperture [%]. In this work all the physical properties are supposed to be constant, as it has been observed in control tests that taking into account their dependence on temperature does not considerably improve the obtained results and on-line adaptation of only one parameter is also possible. In this way the parameters can be grouped together and equation (1) becomes:

\[
\dot{T} = G_U I \left[ 1 - \frac{\sin \left[ \alpha_0 \left( 1 - U/100 \right) \right]}{\sin \alpha_0} \right] + G_T \left( T^4 - T_e^4 \right) + G_T \left( T - T_e \right)
\]

where:

\[
G_T = \frac{\alpha_c S_a}{mC_e}, \quad G_T = \frac{\alpha_0 S_a}{mC_e}, \quad G_U = \frac{S_f(90\%)}{S_f(90\%)} \frac{T^4}{mC_e}
\]

In practical cases, \( \rho_b \) and \( \rho_c \) are measured before a test (typical values are 75% and 95%), while \( G_U^\star \), \( G_T^\star \) and \( G_T \) can be estimated with a standard least squares method. Resulting values are \( G_U^\star = 5.6 \cdot 10^{-3} \text{[m²KJ}^{-1}] \), \( G_T^\star = -5 \cdot 10^{-13} \text{[s}^{-1}\text{K}^{-3}] \) and \( G_T = -3.5 \cdot 10^{-4} \text{[s}^{-1}] \). The comparison between historical data and the calibrated model shows that the mean absolute percentage error is less than 2%, while the maximum relative error is 7% (Beschi, 2010), see Figure 2 as an example. The shutter aperture has a range [0%-100%]. In addition, the maximum velocity of the shutter aperture is limited to 5%/s. In any case, the presence of a vacuum chamber (Minivac) limits the maximum admissible velocity. In fact, a fast shutter aperture can generate a thermal shock in this equipment. The slew rates are therefore set equal to 0.5%/s for the positive velocity and -2%/s as the negative value. The negative value is greater than the positive one because if there is a large radiation increment it is necessary to close rapidly the shutter to prevent thermal shocks.

![Comparison: nonlinear model vs. real output](image)

**Fig. 2.** Comparison: nonlinear model vs. real output

3. GPC-BASED STRATEGY

3.1 Basic algorithm

The disturbance rejection task is addressed by means of GPC (Camacho and Bordons, 2004). The control signal is the sum of two terms. The first one is a feedforward action \( U_{fb}(t) \) which is precalculated, with the hypothesis of perfect model and a solar radiation equal to the theoretical value \( I_{th} \) (selected equal to 900Wm⁻², which is the average annual radiation in Almería), in order to obtain the corresponding output \( T_{fb}(t) \) equal to the set-point value. If the actual values of the temperature and its derivative are known, the value of the theoretical shutter aperture
The GPC strategy utilises a Controller Auto-Regressive Integrated Moving Average (CARIMA) model. This model is a good approximation of many single-input single-output plants around an equilibrium point: \( \Delta A(z^{-1})y(t) = z^{-d}B(z^{-1})\Delta u(t-1) + C(z^{-1})e(t) \) (3) where \( d \) is the dead time of the system, \( y(t) \) is the output of the plant, \( u(t) \) is the control action, \( e(t) \) is a zero mean white noise, \( A, B, C \) are adequate polynomials in the backward shift operator \( z^{-1} \) and \( \Delta(z^{-1}) = 1 - z^{-1} \) (Camacho and Bordóns, 2004). Considering smooth nonlinear dynamics (as those provided by the solar furnace model), the output prediction can be approximated by the superposition of the forced and free responses (Camacho and Berenguel, 1994), \( y = Gu + f \) where \( y \) is the vector containing future ahead predictions of the system output on data up to time \( t \), matrix \( G \) is built by the process open-loop step response coefficients \( g_i \), \( f \) represents the plant free response and \( u \) is the vector of the future control increments obtained from the solution of the GPC optimization problem described below.

To obtain the furnace linearised model, two new variables are introduced:

- \( y(t) \) defined as the error between the plant temperature \( T(t) \) and the model temperature \( T_{th}(t) \);
- \( i(t) \) defined as the difference between the real radiation \( I(t) \) and \( I_{th} \).

Using the furnace model shown in Section 2 and the definition of \( i(t) \) and \( y(t) \) it is possible to write:

\[
G_U (I_{th} + i(t)) \left[ 1 - \frac{\sin \left( \alpha_0 \left( 1 - \frac{U_{th}(t)+u(t)}{100} \right) \right)}{\sin \alpha_0} \right] + G_T \left( \left( T_{th}(t) + y(t) \right) + T_e \right) + G_T \left( T_{th}(t) + y(t) - T_e \right) = \frac{dT_{th}(t)}{dt} + \frac{dy(t)}{dt}
\] (4)

As in (Berenguel et al., 1999), this equation can be simplified and linearised as:

\[
\frac{dT_{th}(t)}{dt} + \frac{dy(t)}{dt} + \frac{\alpha_0}{100} \frac{\cos \left( \alpha_0 \left( 1 - \frac{U_{th}(t)+u(t)}{100} \right) \right)}{\sin \alpha_0} y(t) + \alpha_0 Cu(t) + (4G_T T_{th}^3(t) + G_T) y(t) = \frac{dy(t)}{dt}
\]

Equation (5) describes the linearised model around the actual operating point. The transfer function between \( u(t) \) and \( y(t) \) has the following form:

\[
\frac{Y(s)}{U(s)} = \frac{K}{\tau s + 1}
\]

where:

\[
K = \frac{\tau G_U I_{th}}{100 \sin \alpha_0} \cos \left( \alpha_0 \left( 1 - \frac{U_{th}(t)+u(t)}{100} \right) \right)
\]

and

\[
\tau = \frac{1}{4G_T T_{th}^3(t) + G_T}
\]

The values of \( K \) and \( \tau \) resulting for different values of the temperature \( T_{th} \) are plotted in Figure 4, where the smooth nonlinearity of the process appears. Notice that for generating the figures the steady-state value of \( U_{th} \) for each temperature \( T_{th} \) has been used.

The transfer function can be discretised as: \( y(t) = ay(t-1) + bu(t-1) \) with \( a = e^{-t_s/\tau} \) and \( b = K(1-a) \), where \( t_s \) is the sampling period. The step response coefficients can be easily determined as: \( g_i = \frac{1}{\tau} (a^{i-1} - a^i) b \).

The GPC cost function \( J \) to be minimised in this case with respect to the future control increments is

\[
J = \sum_{j=N_1}^{N_2} \left[ y(t + j|t)|^2 + \sum_{j=1}^{N_2} \lambda(j) [\Delta u(t + j|t)]^2 \right]
\]

which represents the sum of two contributions: the first one to tries to minimise the distance between the actual and the theoretical temperature trajectory in a temporal horizon between times \( N_1 \) and \( N_2 \); the second one measures the control effort in a control horizon \( N_u \). The two terms are weighted with the parameter \( \lambda(j) \). As the dead time of the process is negligible, suitable values for \( N_1, N_2 \) and \( N_u \) are \( N_1 = 1 \) and \( N_2 = N_u = N \). The horizon \( N \) has to be chosen big enough to consider the complete system dynamics. The parameter \( \lambda \) is usually supposed constant for all the horizon. The sampling period \( t_s \) has been fixed.
to 3 seconds, which is a sufficiently small value in comparison with the linearised system time constant, which varies between about half an hour for low temperatures and a few minutes around 1000°C (see Figure 4). The horizon $N$ has therefore been fixed to 40. The prediction time is smaller than the time constant, but it is necessary to remember that the linearisation is a good approximation only near the operating point and therefore a long term prediction is not sensible. For example, if the solar furnace works with a temperature of 200°C and it must follow a ramp of 20°C/min$^{-1}$, after the prediction time (two minutes) the time constant decreases by 10%. Moreover, the system is subjected to fast disturbances coming from the solar radiation and thus using a prediction of the solar radiation equal to its actual value would not provide good results if a long prediction horizon is used.

The cost function $J$ can be rewritten as (Camacho and Bordons, 2004):

$$J = u^T \left( G^T G + \lambda I \right) u + 2f^T G U + f^T f.$$  

The constraints considered in the optimisation are the limited amplitude and slew rate of the control signal. In fact it is not possible to guarantee the respect of the output limits because they depend on solar radiation and it is not always possible to compensate its variation because of the actuator’s limit. Thus, an unfeasible solution of the optimisation problem may occur. The control signal limits are denoted as $\mathcal{U}$ as the minimum limit and $\mathcal{U}$ as the maximum limit. They can be written as:

$$l(U - u(t - 1)) \leq H u \leq l(U - u(t - 1))$$

where $H$ is a lower triangular matrix of ones and 1 is a column vector of ones. The slew rate limits of the control signal are $\mathcal{U}$ and $\mathcal{U}$ and their representation is:

$$l U \leq u \leq l U$$

3.2 Nonlinear prediction of free response

In a nonlinear system like the solar furnace the linear approximation is a good model only around the operating point. To obtain a better prediction it would be necessary to use a nonlinear predictive control, but in this way the computational time increases too much. A way to refine the prediction is using a linear model for the forced response, so that the optimisation is still a quadratic programming problem, and to use a nonlinear free response prediction. Although from the theoretical point of view the algorithm is questionable because the superposition theorem is only valid for linear systems, the practical effectiveness for this approach for solar plants with smooth nonlinear dynamics has been demonstrated in (Camacho and Berenguel, 1994). To calculate the nonlinear free response prediction, the nonlinear model is simulated considering that along the prediction horizon, the input to the system is $U_{th} + j|t| + u(t)$ and the radiation equal to $I(t)$ (last measured value). The theoretical temperature $T_{th}(t + j|t|)$ is subtracted from the resulting temperature to obtain the free response of the error $f(t + j|t|)$, as the GPC works to minimize the difference between the model output and the theoretical output (the output of the model when the input is $U_{th}$ and the radiation is $I_{th}$). Notice that $U_{th}$ and $T_{th}$ vary along the horizon. If a temperature profile is fixed, $U_{th}$ is computed by model inversion, while if $U_{th}$ is imposed (for example a ramp until reaching the desired final set-point), the value of $T_{th}$ is computed by using the nonlinear model. For the GPC algorithm, $U_{th}$ acts as an exogenous signal (not modifiable by the GPC controller), and in this case the desired trajectory is considered to be known.

3.3 Gain adaptation algorithm

All model predictive control strategies have a good performance if the model is sufficiently accurate. If there are model mismatches, a way to improve the performance is to adapt the parameters on-line. This strategy must be applied with care because it is possible that the frequency content of the data is not sufficient for a good estimation. In this work the implemented algorithm is as follows: if the error between the prediction and the actual value is bigger than two Kelvin the parameter $G_U$ is set as:

$$G_U(t + 1) = 1 + \frac{T(t) - \hat{T}(t + t - 1)}{1000}$$

where $T(t)$ is the actual plant temperature and $\hat{T}(t + |t| - 1)$ is the last predicted temperature. The parameter can not increase more than the double of the nominal value and it must be greater than the half of the nominal value. This limitation is done for safety reasons. When the prediction error decreases under one Kelvin the parameter keeps its value. It is worth noting that the decision to modify only the parameter $G_U$ has been taken because this parameter has the greatest influence on the system performance and therefore it is important to have an accurate estimation of its value. The estimation error of the other parameters does not affect significantly the performance obtained.

4. CONstrained CONTROL

This section presents an alternative approach for controlling the thermal process in the solar furnace. The basic idea is to use a standard PI algorithm when the operating point is close to the theoretical one and to use a nonlinear control law when the operating conditions are far from the equilibrium. The nonlinear control law explicitly takes into account constraints on the process output (as well as on the process input). The gain adaptation algorithm proposed for the GPC strategy is used also in this context.

4.1 Switching strategy

The switching between the two control algorithms is a critical issue. Indeed, it is necessary to prevent excessive commutations between the algorithms and to guarantee the continuity of the solution. The first problem is solved by using a hysteresis commutation. Thus, the switching from nonlinear to linear PI control occurs when the temperature error is less than 10°C, viceversa, the switching from linear PI to nonlinear control occurs when the error is greater than 20°C. The continuity of the control signal is guaranteed by using an integrator after the switch (Lourenco and Lemos, 2006). As a consequence the output of both the control strategies must be the first derivative of the desired control action.
4.2 PI control

The linear control consists of a standard PI controller (which aims at minimising the difference between the theoretical process output and the actual one) with a constant feedforward signal $U_{th}$, which is devoted to maintain the equilibrium point, that is, the value $U_{th}$ is such as the corresponding output is $I_{th}$, by assuming a perfect model and a radiation equal to the theoretical value $I_{th}$ (Figure 5). A second feedforward action is devoted to the disturbance compensation. Indeed, the continuous system transfer function (6)-(7) linearly depends on the solar radiation. Thus, as shown in (Berenguel et al., 1999), it is convenient to place the feedforward block $I_{th}/I(t)$ in the forward path (i.e., at the output of the PI controller) so that the resulting global transfer function is theoretically “independent” of the solar radiation values.

By denoting the difference between the theoretical output and the actual one as $y(t)$, the control law expression is:

$$u(t) = \frac{I_{th}}{I(t)} \left[ K_p \left( y(t) + 1/T_i \int_{t_0}^{t} y(v) dv \right) + U_{th} \right]$$

where $K_p$ is the proportional gain and $T_i$ is the integral time constant. The first derivative of the control action, which is necessary for the switching algorithm, is:

$$\dot{u}(t) = \frac{I_{th}}{I(t)} \left[ K_p \left( \dot{y}(t) + \frac{1}{T_i} \right) \right] - \frac{I_{th} I(t)}{I(t)^2} u(t)$$

The tuning of the PI parameters have been performed by means of an iterative numerical algorithm that minimises the average value of integrated absolute errors obtained by considering the load disturbance response in three different cases, that is, at three different set-point temperatures.

4.3 Nonlinear control

In order to increase the performance also when the system is far from the operating point, a nonlinear control law has been devised. The rationale of this strategy is to select the desired derivative functions of the output variable and to obtain the control variable by the inversion of the input-output equation. Consider a first-order nonlinear system described by the equation:

$$\ddot{y}(t) = f(y(t), u(t), \dot{d}(t))$$

where $\dot{d}(t)$ is vector of the nonmanipulated inputs. If $f(y,u,d)$ is invertible, it is possible to write:

$$u(t) = g(y(t), \dot{y}(t), \dot{d}(t)).$$

By derivating with respect to the time it is possible to obtain the signal $\dot{u}(t)$ which is necessary for the switching algorithm:

$$\dot{u}(t) = -\frac{\partial g}{\partial y}(y(t), \dot{y}(t), d(t)) \ddot{y}(t) + \frac{\partial g}{\partial \dot{y}}(y(t), \dot{y}(t), d(t)) \dot{y}(t) + \frac{\partial g}{\partial d}(y(t), \dot{y}(t), d(t)) \dot{d}(t)$$

The choice of $\ddot{y}(t)$ and $\dot{y}(t)$ can be done by plant constraints, empirical considerations or operators experience. The instantaneous values of $\ddot{y}(t)$ and $\dot{y}(t)$ are chosen with the following procedure, where $y_M$ and $\ddot{y}_M$ are the maximum limits of the derivatives:

1. The last output derivative is calculated by the equation (10) performed at the time $t - t_s$;
2. if $y(t) - y_{th}(t) < 0$
   (a) if $\dot{y}^2(t - t_s) \geq 2y_M |y(t) - y_{th}(t)|$ then $\ddot{y}(t)$ is set equal to $-\ddot{y}_M$;
   (b) elseif $\dot{y}(t - t_s) < \ddot{y}_M$ then $\ddot{y}(t)$ is set equal to $\ddot{y}_M$;
   (c) elseif $\dot{y}(t - t_s) > \ddot{y}_M$ then $\ddot{y}(t) = -\ddot{y}_M$;
   (d) else $\ddot{y}(t)$ is set to zero;
3. elseif $\dot{y}(t - t_s)^2 \geq 2y_M |y(t) - y_{th}(t)|$ then $\dot{y}(t)$ is set equal to $\ddot{y}_M$;
4. elseif $\dot{y}(t - t_s) > -\ddot{y}_M$ then $\dot{y}(t)$ is set equal to $-\ddot{y}_M$;
5. elseif $\dot{y}(t - t_s) < -\ddot{y}_M$ then $\ddot{y}(t)$ is set equal to $-\ddot{y}_M$;
6. else $\ddot{y}(t)$ is set to zero;
7. the desired first derivative is set as $\dot{y}(t) = \dot{y}(t - t_s) + \ddot{y}(t) t_s$;
8. the derivative of the control action is calculated by expression (11).

In the solar furnace of Almería, the operators suggest $40^\circ$C/min as maximum peak of temperature’s derivative, the second derivative peak is chosen to $120^\circ$C/min$^2$.

5. SIMULATION RESULTS

The proposed control methodologies have been tested with a set-point temperature of $200^\circ$C, $600^\circ$C and $1000^\circ$C, in order to highlight the performance achieved in different operating points. In these cases the values of the linearised system state constant are respectively (see (8)) $1780$ s, $594.8$ s, and $223.3$ s. The simulations have been made by using the radiation of a cloudy day and, in addition, constant and variable errors have been introduced in the values of the model parameters. In particular, the mean errors of the parameters $G_T$, $G_T^+$, $K_T^+$ are respectively: $+50\%$, $+10\%$ and $-20\%$. The variable errors have a normal distribution with standard deviation of $10\%$.

The two methodologies proposed in the previous sections are compared with a standard PI controller with the parameters tuned according to the optimisation technique described in subsection 4.2. Figures (6)-(8) represent the evolution of temperature, shutter aperture and radiation during the simulations, for the three considered cases. It appears that the GPC provides the fastest settling time, while the constrained control strategy has, as expected, a greater limitation of temperature derivative, because of the selected output constraints. This aspect is considered
Fig. 6. Simulation results for the set-point temperature of 200°C. Solid line: PI controller. Dashed line: GPC. Dash-dot line: constrained control.

Fig. 7. Simulation results for the set-point temperature of 600°C. Solid line: PI controller. Dashed line: GPC. Dash-dot line: constrained control.

important by the furnace operators. In fact, in this way the equipment presents a smaller thermal stress. Figure 9 represents the adaptation of the gain $G_U$ with the constrained control strategy for the case of the set-point temperature of 1000°C. Similar results are obtained in the other cases and for the GPC-based method. It can be noted that the value of the parameter is conveniently updated in order to compensate for the estimation error.

6. CONCLUSIONS

In this paper two control methodologies have been proposed for the disturbance rejection in a solar furnace. While the GPC-based control provides the best settling time in general, the constrained control method presents the remarkable feature that the constraints on the process input and output are satisfied, thus avoiding a possibly dangerous thermal stress of the material. Future work will include the output constraints in the GPC controller (treatment of unfeasibility problems caused by solar radiation variations through reference governor approaches).

as far as experiments on the real solar furnace in order to verify the effectiveness of the control techniques in practical cases.

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