Automatic Control of a Solar Furnace for Rapid Temperature Changes
Alexandre Lobo Fernandes

Abstract—Solar furnaces are devices used to study, test and transform materials through exposure to highly concentrated solar energy. In this paper, a study on automatic control strategies for solar furnaces is done, with the goal of being able to produce fast temperature variations, usually required to perform thermal stress tests. The process to be controlled brings about many interesting control challenges, such as non-linearities in the sample’s thermal dynamics and constant disturbances caused by the natural variation of the available solar power.

A cascaded controller architecture is explored, separating the problem into two smaller ones. With this architecture, an inner controller is responsible for assuring a desired radiation flux on the furnace’s focus, compensating the variations on the available power. The outer controller handles the actual control of the temperature, having as output the desired radiation flux which is assured by the inner controller.

The variation of the sample’s dynamics with temperature suggests the use of a multi-model adaptive control approach, resulting in the design of a set of local controllers for different working temperatures. Root-locus based design of a PI controller, pole placement control based on polynomial techniques and linear quadratic optimal control approaches are considered for the design of these controllers. It is shown that the last two approaches prove to be able to assure desired performance for many temperature ranges.

Sensitivity and robustness trials are done so as to perceive which approaches best handle model uncertainty and rejection of disturbances.

Index Terms—Solar furnace, supervised adaptive control, exact linearization, polynomial control, optimal control.

I. INTRODUCTION

Due to the recent demand on proper and conservative energy use, solar powered applications have been the subject of extensive research in the last decades. One such application is the use of solar furnaces for the testing and synthesis of materials, which would otherwise require great amounts of power.

In order to attain the desired temperatures, a skilled operator must define the aperture of a motorized shutter system, which allows manipulation of the amount of radiation at the focus, and attempt to properly adjust this value as the temperature rises. Several difficulties arise when doing this, as the amount of solar power that is available changes naturally along time, mainly due to the Sun’s apparent movement or weather conditions. Also, because the temperature at which materials are tested is many times close to their melting point, it is crucial not surpass this value, which is quite difficult when performing rapid temperature variations (thermal stress tests).

The goals of this work are then to provide an automatic control solution that allows tracking of desired temperature references, while also being able to subdue samples to rapid temperature variations and robust enough not be affected by available solar power variations.

A. Plant Description

This work is done based on the characteristics of the 6kW solar furnace on the Odeillo solar research complex, in France. This furnace is comprised of mainly four components that affect the temperature dynamics to be controlled. They are the heliostat, the parabolic concentrator, the shutter and the sample’s thermal dynamics.

The heliostat is a moving mirror that is used to guide the sun light onto a concentrator. This device is in closed-loop with a controller that allows it to track the Sun’s position in the sky, so that the direction taken by the reflected beams that reach the concentrator is always the same. This is important because, otherwise, the furnace’s focus would be displaced.

The parabolic concentrator redirects the received solar radiation onto the focus, where the sample is to be placed. In between the focus and the concentrator, a shutter is used to manipulate the amount of incident radiation that reaches the sample. This device plays a critical role as it acts as an actuator for the temperature control system, and it is itself a closed loop system, as its motor is connected to a driver which receives desired positions for the opening of the shutter blades.

The sample’s temperature is measured by thermocouple attached to its lower surface. With these measurements, and given a reference for desired sample temperature, a controller is able to command the shutter so as to appropriately adjust its aperture, thereby controlling the incident radiation on the sample. This allows controlling of the sample’s temperature.

B. State of the Art

Research on automatic control of solar furnaces began with [1], where a non-linear model for the sample’s thermal dynamics is built and validated. A feedforward controller is designed which is able to compensate variations on the available solar power, which makes up the most influencing disturbance of the process. An adaptive PI controller used to perform temperature control while being able to counter the process’s non-linearities, as its properties change with the working temperature.

In [3], identification methods are used on actual shutter data in order to obtain a model for its dynamics, revealing that the device presents some non-linear behavior.

A cascade controller architecture is explored in [2], where an inner controller acts directly upon the shutter subsystem and the outer controller aims at controlling the sample temperature. The inner controller compensates variations on the solar power
and linearized the actuation of the process, simplifying the design of the outer controller. The temperature controller
in this approach was again a PI controller with a constant integral gain and a proportional gain that varied with the
working temperature. The stability of the closed system with both controllers is proved through the use of the singular
perturbation method based on Lyapunov theory. In [4], the
same authors explore a control law for temperature obtained
through the exact linearization technique.

Other solar furnace control techniques studied include fuzzy
control [10], used to cope with the many different uncertainties
that affect the dynamics of this process. [11] explores con-
troller design based on Disturbance Accommodating Control
theory, providing a solution that handles both strong distur-
bances and process non-linearities efficiently.

II. Modelling

In order to design a controller for the plant, it is first
necessary to build models for both the shutter subsystem and
the samples’ thermal dynamics.

A. Shutter Model

The shutter is comprised of a motor, gears and a set of
blades that define the aperture of the shutter. The positioning
of the blades is described by the angle they form with the
horizontal plane. Below $\theta_0 = 25^\circ$, no light passes through the
shutter.

The shutter subsystem is describable by two major charac-
teristics, its dynamics and its static function, which describes
the relation between the shutter’s blade angles and its aperture.
To model the shutter dynamics, data from the 6KW furnace
was used, which had the step responses of the shutter to
$10^\circ$ increase and decrease commands, for the entire range of
possible angles for the device above $\theta_0$, $[0, 60]^\circ$. It could be
seen from this data that the dynamics of the shutter change,
depending on the blades position. This non-linear behavior is
likely due to the varying torque on the gears as the blade’s
angle increases.

A linear model was developed by considering the $[20, 30]^\circ$
range and approximating the shutter dynamics for this range
by a second order transfer function:

$$\ddot{z}(t) + 2\xi \omega_n \dot{z}(t) + \omega_n^2 z(t) = \omega_n^2 u_{shunt}(t)$$  (1)

With parameters valued at $\xi = 0.7$ and $\omega_n = 20$. $z(t)$ is the
normalized angle of the shutter, with values in $[0, 100]$, and
$u_{shunt}(t)$ is the command for the normalized angle received
by the shutter subsystem. This model was validated with the
actual shutter data, giving a mean square error of 5.61%.

A more accurate model for the shutter dynamics was also
developed. By resorting to identification techniques, a bank of
models was constructed, each covering the dynamics for an
angle range. A switching mechanism was designed to assure
that, as the shutter angle changed, the appropriate model was
selected to generate the output. This resulted in much better
approximation than (1), but it was not practical for controller
design.

Regarding the shutter’s static function, geometric relations
lead to the following equation for the percentage of shutter
openness, given the blades’ normalized angle:

$$S(z(t)) = \frac{\cos (\theta_0 + z(t)(90 - \theta_0)/100)}{\cos \theta_0}$$  (2)

B. Thermal Dynamics Model

A model for the temperature dynamics of the sample based
on an energy balance was built. In table I, all necessary para-
eters for this model are presented, assuming that the sample
under test is a disk of $A_2O_3$. The sample’s temperature, $T_s(t)$,
is described through the following differential equation:

$$\frac{dT_s(t)}{dt} = -\alpha_1 [T_s(t) - T_{sur}(t)]$$  
$$- \alpha_2 [T_s(t) - T_{air}(t)]$$  
$$+ \alpha_3 u(t)$$  (3)

Where $T_{air}$ and $T_{sur}$ are the temperature of the air and the
temperature of the surroundings, respectively. The signal $u(t)$
is the amount of incident radiation that reaches the sample,
given by $u(t) = G_s(t)S(\theta(t))$. The coefficients $\alpha_1$, $\alpha_2$ and
$\alpha_3$ are defined as:

$$\alpha_1 = \frac{\epsilon \sigma A_s}{C_p m}$$
$$\alpha_2 = \frac{h_{conv} A_s}{C_p m}$$
$$\alpha_3 = \frac{\alpha_A g r h_f}{C_p m}$$

The following equations describe the convection factor,
specific heat and emissivity of the $A_2O_3$ dependency on the
sample temperature:

$$h_{conv}(T_s) = 1.32 \left( \frac{\|T_s - T_{sur}\|}{L_c} \right)^{0.25}$$  (4)

$$C_p(T_s) = 1.0446 \times 10^3$$
$$+ (1.742 \times 10^{-4} T_s - 2.796 \times 10^{4} T_s^{-2}) \times 10^3$$  (5)

$$\epsilon(T_s) = -3.3333 \times 10^{-4} (T_s - 800) + 0.65$$  (6)

In order to apply linear control techniques, the model in
(3) is linearized around a working temperature $T_s = T_0$
using Taylor’s Theorem for smooth non-linear functions.
The resulting first order model is described by the following
transfer function:

$$\frac{T_s(s)}{u(s)} = \frac{b}{s + \alpha}$$  (7)

With $a = 4\alpha_1 T_0^3 + \alpha_2$ and $b = \alpha_3$. Now, because the
thermocouple attached to the sample provides noisy tempera-
ture measurements with an approximate variance of , a low
pass filter is designed in order to reduce its effect on the
control loop. This filter was designed to have unitary static
TABLE I
PARAMETERS FOR THE THERMAL DYNAMICS MODEL. THE SAMPLE IS ADMITTED TO BE OF Al₂O₃.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_p$ [J/K g⁻¹ K⁻¹]</td>
<td>Specific heat</td>
<td>$e_2(5)$</td>
</tr>
<tr>
<td>$m$ [kg]</td>
<td>Mass of the sample</td>
<td>$2.651 \times 10^{-3}$</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Emissivity of the material</td>
<td>$e_2(6)$</td>
</tr>
<tr>
<td>$\sigma$ [W/m² K⁻⁴]</td>
<td>Stephan-Boltzmann constant</td>
<td>$5.67 \times 10^{-8}$</td>
</tr>
<tr>
<td>$A_s$ [m²]</td>
<td>Exposed area of the sample</td>
<td>$7.068 \times 10^{-4}$</td>
</tr>
<tr>
<td>$h_{conv}$ [W/m² K⁻¹]</td>
<td>Convection factor</td>
<td>$e_2(4)$</td>
</tr>
<tr>
<td>$\alpha_s$</td>
<td>Solar absorptivity of the material</td>
<td>0.14</td>
</tr>
<tr>
<td>$g_f$</td>
<td>Solar furnace gain</td>
<td>2525</td>
</tr>
<tr>
<td>$h_r$</td>
<td>Heliostat and concentrator mirror gain</td>
<td>1</td>
</tr>
<tr>
<td>$G_s(t)$</td>
<td>Solar radiation flux (max. value)</td>
<td>$1 \text{KW/m}^2$</td>
</tr>
</tbody>
</table>

Fig. 1. Cascade control architecture.

gain and a cutoff frequency \(\omega_f = 10 \times (4a_1 T_0^2 + \alpha_2)\) [rad, s⁻¹], for \(T_0 = 1000\) K. The process to be controlled can then be described by the sample-filter dynamics as:

\[
\frac{T_f(s)}{u(s)} = \frac{b \omega_f}{s^2 + (a + \omega_f)s + a \omega_f} \tag{8}
\]

\(T_f\) being the filtered sample temperature.

III. CONTROLLER ARCHITECTURE AND DESIGN

Using the cascaded architecture shown in Fig.1, an inner controller was designed to both linearize the actuation of the process and to compensate variations of the available solar power, receiving desired radiation levels at the focus and acting on the shutter aperture. The outer controller controls the sample’s temperature, defining the required levels of radiation.

A. Inner Controller

The inner controller was designed through the exact linearization technique[2]. Assuming that the desired closed loop dynamics are the same as the shutter’s, and defining \(r(t)\) as the amount of radiation flux at the output of the shutter subsystem and \(R(t)\) is the desired value for this quantity, the following control law was obtained:\footnote{The time dependency of the signals was removed in order not to overburden the notation.}

\[
u_{\text{shut}} = (a_2^2 (R - r) - 2 \xi \omega_n r - \delta S) S - \dot{z} S' [2G_s + G_s (S' - S^2 \omega_n)] + z G_s S^2 \omega_n^2 / G_s S' \omega_n^2 \tag{9}
\]

\[
\begin{align*}
|S| & = S(z) \bigg|_{z(t)} \quad S' = \frac{dS(z)}{dz} \bigg|_{z(t)} \quad \text{and} \quad S'' = \frac{d^2 S(z)}{dz^2} \bigg|_{z(t)} \quad \text{The signals} \quad \tilde{G}_s(t) \quad \text{and} \quad \tilde{G}_s(t) \quad \text{can be obtained by} \\
\text{filtering the} \quad \text{the inner closed loop system. One can see that during the} \quad \text{interval [5, 15]s, because there is not enough available power} \\
\text{to satisfy the desired value, the shutter remains fully open} \quad \text{and the curve of the available solar power can be seen at} \\
\text{the output of the device. The controlled system displays good} \quad \text{performance for the rest of the simulation, as it is able to keep} \\
\text{a steady flux on the output despite constant variation of the} \quad \text{available power, while still keeping track of the reference} \\
\text{with significant speed.}
\end{align*}
\]

B. Outer Controller

For the design of the outer (temperature) controller, three approaches were considered, based on the linear model of the plant in (8). The goals for this controller are to accurately follow a given reference temperature and provide fast responses with minimal overshoot, particularly on the [800, 1500]K temperature range, for which many of the tests undertaken in this plant are done.

1) PI approach: Assuming a standard PI controller defined by \(u(t) = K_p e(t) + K_i \int \epsilon(\tau) d\tau\), the following transfer function defines the closed loop dynamics:

\[
\frac{T_f(s)}{T_r(s)} = \frac{K_p \omega_f (s + K_i)}{s^3 + (a + \omega_f)s^2 + (a \omega_f + K_p \omega_f)s + K_p K_i \omega_f} \tag{10}
\]

Where \(T_r\) is the desired reference temperature. Through root-locus analysis, it was determined that for \(K_p = 1.4\) and \(K_i = 1.1\), for \(T_0 = 900\), the closed loop poles were placed in such a way that one pole was nullified by the controller’s zero and 2 complex conjugate poles dominate the dynamics, resulting in an overshoot of 1.53% and rise time of about 25s for a simulation with the linear model. A simulation was also done with this controller using the non-linear model of the plant (stabilized at \(T_0\)) with the inner loop designed previously.
Examples of relevant facts. Through the use of the theory in [6], controller polynomials $R(s)$, $S(s)$ and $T(s)$ are defined to achieve the desired closed-loop in 11, using the linearized model for the plant at $T_0$. When tested with the non-linear plant, this controller proved to be capable of maintaining the desired dynamics for the temperature range $[800, 1500]K$. This is shown in fig. 5 for part of this range.

By analyzing the pole displacement along the various temperature ranges, one can observe some relevant facts. Through the polynomial $T$, the controller imposes two fixed zeros on the closed loop transfer function, also adding two other poles through polynomials $R$ and $S$. In the working temperature the controller is designed for, $T_0$, the two zeros are placed such that two of the poles are compensated, while the other two remaining poles are left to define the desired closed loop dynamics. In fig. 6 the pole locations for three temperatures are shown. One can see that the poles that are to be nullified by the zeros start closer to the origin and, when the temperature reaches $T_0$ (1000K for this example), they merge on the real axis together with the zeros, leaving the two conjugate poles on the left defining the dynamics. For higher temperatures, the nullified poles drift apart on the real axis and on opposite directions. However, the presence of the two zeros is enough to compensate the effect of the slowest pole, denying its dominance over the dynamics. This is possible because the slowest pole does not move far enough from the zeros, unlike what happened with the PI example.

3) Optimal Control: An optimal control approach is implemented according the schematic seen in 7. This technique is based on linear quadratic (LQ) regulator theory[8]. The state space is considerer to be $z = [x_2 \ x_1 \ x_1]^T$, where state $x_1$ is the sample’s temperature and state $x_2$ is the filtered sample’s temperature and $x_1 = T_1 - x_2$. The working temperature considerer is $T_0 = 1000 K$. 

![Fig. 3. PI controller performance for ranges below $T_0$.](image)

![Fig. 4. Polynomial control scheme.](image)

![Fig. 5. Polynomial control performance in the range $[1100, 1500]$.](image)

![Fig. 6. Pole locations of the closed loop system with a polynomial controller for 3 temperatures.](image)
Fig. 7. Implementation scheme of the optimal controller.

![Diagram](image)

Fig. 8. Reference and temperature for the optimal controller.

![Graph](image)

Fig. 9. Incident radiation for the optimal controller.

![Graph](image)

The following gains for the controller are obtained:

\[
K_2 = 9.4095, \quad K_1 = 13.0851, \quad K_1 = -3.1623
\]

Of course the noise from the sensor measuring \( x_1 \) (unfiltered temperature) is greatly amplified by \( K_1 \), producing unacceptable values for the input of the inner controller. As such, a Kalman Filter was assembled to obtain estimates that are less noisy. In figs.89 a simulation of this controller’s performance with the non-linear model with added Kalman Filter is shown. An anti-windup mechanism was also added so as to prevent problems caused by saturation.

Much like what was observed with the polynomial controller, the optimal controller proved to maintain a good performance for the whole range of temperatures. This can again be explained through an analysis of the closed-loop pole variation with temperature, which can be done by inspection of table II. It should be noted that this control scheme imposes a numerator in the closed-loop transfer function with insignificant coefficients, other than the zero order one. This means that the system can be considered not to have any zeros.

Before \( T_0 = 1000K \), poles 1 and 2 are complex conjugate, but placed well below the value of pole 3, which dominates the dynamics of the system. For \( T_0 = 1000K \), the temperature for which the controller is tuned, the three poles take real values, yet pole 3 is still the slowest, imposing dynamics only slightly faster than for lower temperatures. For the temperatures above \( T_0 = 1000K \), poles 2 and 3 form a complex conjugate pair that now dominates the dynamics, but the overshoot caused by this pair does not go beyond 1% for \( T_0 = 1500K \) and the system’s rise time does not change much from its previous values.

4) Multi-Model Switching Control: A Supervised Multi-Model Switching Control (SMMAC) was designed in order to improve the performance of the controllers designed through III-B1. A supervisor process infers from the process output which controller, from a bank of fixed gain PI controllers, is the most appropriate one for the current working region of the plant.

A bank \( C = \{C_{ij}, j = 1, \ldots, N \} \) of PI controllers was designed, each one appropriately tuned so as to assure an acceptable performance in the temperature range its designed for. Each selected controller \( C_p \in \mathcal{C}, p \) being the selection index outputted by the supervisor, should comply with a set of performance criteria which are meant to be kept throughout the different temperature ranges. Being that most of the relevant tests in thermal stress are performed in the \([800, 1500]K\) temperature range, this interval will be considered the entire temperature workspace \( \mathcal{R} = \{R_{ij}, j = 1, \ldots, N\} \).

### Table II

<table>
<thead>
<tr>
<th>( T_0[K] )</th>
<th>Pole 1</th>
<th>Pole 2</th>
<th>Pole 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>800</td>
<td>-0.635 + 0.222i</td>
<td>-0.635 - 0.222i</td>
<td>-0.228</td>
</tr>
<tr>
<td>900</td>
<td>-0.606 + 0.144i</td>
<td>-0.606 - 0.144i</td>
<td>-0.244</td>
</tr>
<tr>
<td>1000</td>
<td>-0.669</td>
<td>-0.476</td>
<td>-0.274</td>
</tr>
<tr>
<td>1100</td>
<td>-0.745</td>
<td>-0.320 + 0.073i</td>
<td>-0.320 - 0.073i</td>
</tr>
<tr>
<td>1500</td>
<td>-0.853</td>
<td>-0.210 + 0.152i</td>
<td>-0.210 - 0.152i</td>
</tr>
</tbody>
</table>
Fig. 10. Implementation scheme of the SMMAC controller.

In table III, the bank of designed controllers is presented. Their design was done having the performance criteria of keeping the closed-loop responses with a similar peak time amongst each other, while maintaining the overshoot within acceptable values. The temperature workspace was divided into subregions $R_j \subset \mathbb{R}$ of $\Delta R[K]$ each, with each corresponding controller being drawn assuming a working temperature valued at its mean. It was observed that each PI held the performance it was designed to achieve for approximately $50K$ above and below its operating temperature, defining $\Delta R = 100K$.

Figure 10 shows how the complete switching control scheme is assembled, where an anti-windup mechanism is included. The representative block labeled Plant comprises the sample’s dynamics, the low-pass filter for the temperature and the inner control loop for the shutter. Notice that, in this scheme, an integrator block is common to all controllers inside bank $C$. This allows for smoothness of the actuation signal when switching occurs[5], [9].

The supervisor process infers from the current temperature of the sample which of the controllers in the bank should used. This decision is made through Algorithm 1. By observing the value of the measured filtered temperature, and taking into account the current controller in use, the supervisor infers if the current temperature has either gone above, below or stayed within the current controller’s temperature range. The supervisor’s output, index signal $\sigma = p \in P$, is then the one corresponding to the correct controller for each of these three situations.

Because there is the possibility of overshooting and due to the presence of noise in the signal used by the supervisor to infer the current temperature range, it is important to add some hysteresis $h$ on the values that define the limits for each region. Assuming that a temperature range $R_p$ is defined by its upper and lower limits, $R_u^p$ and $R_l^p$, the supervisor’s decision logic is done in such a way that if the controller $C_j$ is selected, and if the temperature signal $T_f$ surpasses $R_{j+1}^u + h$, controller $C_{j+1}$ is selected. On other hand, if the temperature signal $T_f$ undergoes $R_{j-1}^u - h$, controller $C_{j-1}$ is selected. This prevents the effect of chattering (or excessive commuting) between controllers in bank $C$, ensuring closed loop stability.

Given the values of noise and maximum overshoot, the selected value for the hysteresis level was $10K$, which will be shown to guarantee the above mentioned conditions.

Algorithm 1 Supervisor’s switching logic

Require: $j \in P$, $\mathbb{R}$, $T_f$

\[
\sigma = j
\]

if $T_f \leq R_{j-1}^u - h$ then

\[
\sigma = j - 1, \sigma \geq 1
\]

else if $T_f > R_{j+1}^u + h$ then

\[
\sigma = j + 1, \sigma \leq N
\]

end if

Simulations were done proving that this approach guarantees a relatively constant performance for the entire range $\mathbb{R}$. In figs. 11, the performance of the switching controller is compared to that of fixed controller $C_4$, revealing that the switching system d. In fig.12 the supervisor’s output signal, i.e. the selected controller along time, is shown for better understanding.

IV. Sensitivity Tests

The model used for designing the controllers assumed correctness of all sample’s properties. It is well known however, that knowing accurately the properties of a given substance can
not be given as granted, which stresses out the importance of testing these controllers under some uncertainty. Having this in mind, trials were done using the developed SMMAC, LQ based optimal an polynomial controllers, in order to understand which controllers were less sensitive to parameter error. Figure 13 shows a comparison simulation aimed at evaluating the three controllers’ performance under the conditions they were previously tested (correct model parameters).

As a representative situation, an increase on the estimated emissivity value $\epsilon$ of the alumina is considered, which is done by increasing the values obtained through equation (6) by 30%. This increase in emissivity results in a shift of the system’s original pole, approximately defined by the the linearized model parameter $a$, which becomes larger. In figure 14 the resulting effects of this parameter change on the closed loop response for the three controllers is shown, assuming a constant $G_s = 1000 W/m^2$.

It can be seen that the closed loop response is slower for all controllers, though only significantly on the SMMAC one. This is expected to occur if the results obtained during the design phase of the three control approaches are taken into consideration.

As this parameter change results in a pole displacement to a larger value, much like what happened with temperature increase due to the plant’s non-linear properties, the plant’s static gain and time constant are decreased. It was shown during the design phase that fixed PI controllers suffered performance degradation for system’s pole changes, while the polynomial approach and LQ based controllers had their performances hardly altered. For this reason, the various PI controllers with fixed gains that make up the SMMAC controller will be less appropriate for keeping the desired performance on their respective regions.

V. CONCLUSION

This paper summarizes the methodologies used to plan and design control strategies to be applied in a solar furnace. It was explained, through an analysis of closed loop pole displacement with temperature, that for both the polynomial and LQ optimal controllers, different temperature ranges resulted in minor changes in the closed loop dynamics. However, an important remark must be made as these conclusions were taken for the temperature range in question, [800, 1500]$K$. For instance, concerning the polynomial controller, the behavior of the closed loop dynamics changes significantly for the lower temperature ranges, as the dynamics as mostly defined by a pair of closed loop poles located closer to the origin.

The controller designed based on linear quadratic regulator theory demanded the use of an optimal filtering technique, since this approach assumed full state feedback and the process’s noise was greatly amplified, possibly damaging the shutter’s components. With a Kalman Filter put to use, the controller still proved to perform very well, though it should be taken into account that this addition demands computational resources that other controllers would not.

Regarding remarks on the developed switching adaptive controller, a test with a ramp input proved this approach’s worth as it assured the same rising speed as a single PI controller but no overshoot was detected when the reference was again constant. For material tests with steady temperature increases but ending up very close to the sample’s melting point, this behavior is most valuable.

However, considering the trials made for sensitivity to parameter change, it was shown that the switching controller approach had major disadvantages. A its fixed local controllers are designed for specific pole positions, differences in the pole positioning along the different temperature ranges quickly render the various fixed PI’s inappropriate.

REFERENCES


