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Adaptive control of the temperature of a glass furnace

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Abstract

This paper describes an application of adaptive generalized predictive control to the regulation of the glass temperature in an industrial furnace operated by the Glaverbel Company (Belgium). Basic features of the algorithm are described and the results show a significant improvement with respect to the previous manual operation of the furnace.

Keywords. Predictive control, Optimal control, Adaptive control, Industrial applications.

1 Introduction

In the last decade, there has been a growing interest for the application of modern control techniques in the glass industry ([GD76], [Fin82], [HHK81], [Mar82], [WD84], [WD87]). Several parts of the glass production process have been automated for many years now, but the glass melting furnace itself remains mainly under the control of human operators. Reasons for this are that glass melting is a highly nonlinear process which can only be accurately modelled by means of partial differential equations whose solution, even in the steady state case, already require an enormous computer effort, which made engineers wonder whether a controller could be designed based on these complicated physical models. On the other hand, since the process of glass melting is very slow, with time constants often of more than 20 hours, the tuning of a controller by trial and error is very difficult. However, the increase of energy costs and the tough competition between glass companies worldwide has made the need for a better product at a lower price more urgent than ever. Studies have shown evidence of a strong relation between the glass quality (bubbles, stones) and the stability of the bottom temperature of the furnace. Also, a more stable bottom temperature allows the furnace to be operated at a lower mean temperature, hence leading to energy savings. For these reasons, the Glaverbel Company launched a research project in cooperation with the University of Louvain in order to develop a bottom temperature controller based on advanced control theory.

This research led to the development of an adaptive predictive controller which has been installed on one of the furnaces of the company and has led to such good performance that the aim is now to install similar controllers on several (if not all) furnaces operated by Glaverbel.

This paper reports the application of modern adaptive techniques to a real industrial environment. It is our feeling that up to now, most of the reported applications of adaptive control have dealt with pilot plants which were kept under supervision of adaptive control experts. This is not the case here and should encourage industries to increase their efforts in this domain.

The paper is organised as follows. Section 2 starts with a description of the process under study and introduces a few notations. In section 3, we briefly discuss some identification results and follow with the description of the control algorithm. Industrial results are presented and commented in section 4. Section 5 concludes.

2 Description of the Process

2.1 The Glass Furnace

The process which is the subject of this report is a glass furnace operated by the Glaverbel Company (Belgium). A basic sketch of the process is shown on figure 2.1. Raw material enters the furnace at one end and melted glass is extracted from the furnace at the other end. The main heating power is obtained through a range of fuel or gas burners across the furnace. Some additional heating is also provided through electrodes sunk into the melt, but this accounts for only a few percent of the total

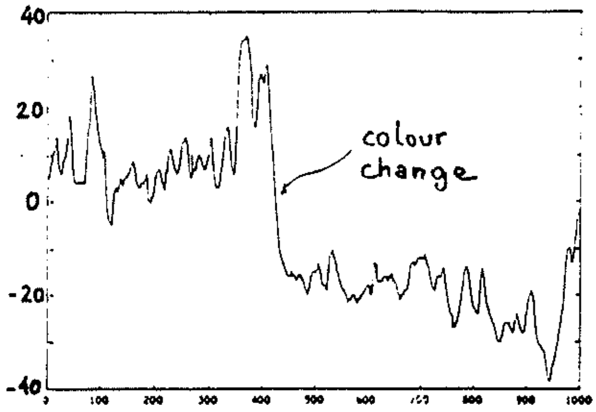

Figure 3.1: bottom temperature under manual control

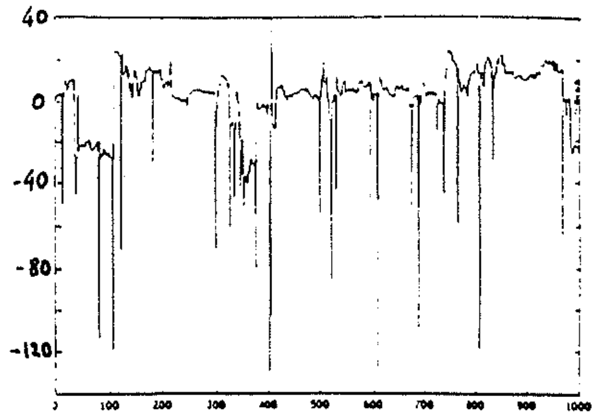

Figure 3.2: pull

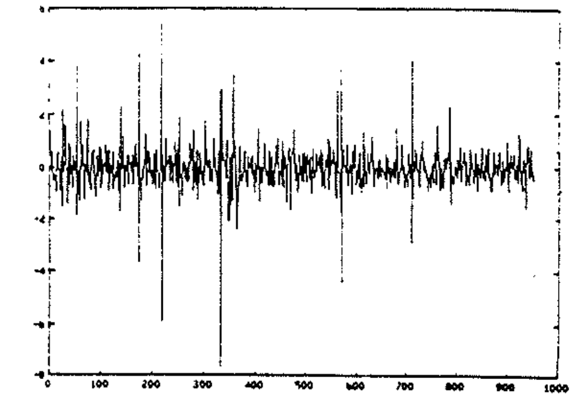

Figure 3.3: prediction errors with an adaptive ARX model

where $e(t)$ represents the prediction error and K is an offset term. $A(q^{-1}), B(q^{-1}), F(q^{-1}), P(q^{-1}), N(q^{-1}), C(q^{-1}), D(q^{-1})$ are all polynomials in the backward shift operator.

This identification study led to the choice of simpler ARX models where the C, D, F and N polynomials are all equal to one. A proper choice of the sampling period had to be done and a one hour sampling period was eventually retained as a good compromise between the need of a rather low sampling rate according to the rules of thumb for control design involving models in the backward shift operator and the wishes of the process engineers to have new control actions computed sufficiently rapidly after important perturbations (like pull changes).

Finally, the identification study led to second order A, B and P polynomials and unit values for the delays $d1$ and $d2$. The performance of such a prediction model is illustrated in the following figures. Figure 3.1 shows identification data of the bottom temperature of the furnace during more than 40 days, the big drop in temperature being the result of a change of glass colour during that period.

Figure 3.2 shows the value of the pull during the same period, and illustrates a specific feature of this process which are the frequent but short drops in pull, corresponding to a change of glass forming machines downstream.

Figure 3.3 represents the one step (i.e. one hour) prediction errors obtained with an adaptive prediction model with forgetting of old data. This figure shows that the model was able to adapt to the change of dynamics which is a result of the change of colour in the furnace, as the magnitude of the prediction errors remains of the same order after the colour change. The standard deviation of the prediction errors was approximately 0.8^oC, compared to a standard deviation of the output signal around 4.0^oC.

3.2 Control Algorithm

Since a basic feature of this process is the major influence of the pull variations, the designed controller takes this specifically into account by dividing the control action $u(t)$ into two terms $u(t) = u_p(t) + u_e(t)$ where the first term is directly computed as a feedforward compensation of the pull variations while the second term is the feedback compensation of all other perturbations acting on the process (including mismodelling). The model equation can hence be rewritten as

$$Ay(t) = Bu_e(t-1) + (Bu_p(t-1) + Pp(t-1) + K) + e(t) \quad (3.2)$$

(here and in the following, we have dropped the arguments of the polynomials for notational convenience).

The *feedforward compensation* of the load is then a static compensation aimed at making the term between brackets vanish[1]:

$$u_p(t) = -\frac{P(1)}{B(1)}p(t) - \frac{K}{B(1)} \quad (3.3)$$

The *feedback compensation* $u_e(t)$ is computed using a generalized predictive control (GPC) algorithm with reference model ([IFF86], [BGW90],

[1] Note that $\frac{P(1)}{B(1)}$ is the static gain of the transfer function $\frac{P(q^{-1})}{B(q^{-1})}$.

([GWZ87]). In order to simplify the presentation of this algorithm, let us suppose for a while that the feedforward compensation is perfect, so that the process model really is

$$Ay(t) = Bu_e(t-1) + e(t) \qquad (3.4)$$

Since this controller is also supposed to handle setpoint changes, we also define a reference model for these setpoint changes by

$$y_r(t) = \frac{BT}{A_r} r(t) \qquad (3.5)$$

to which there corresponds an input reference model

$$u_r(t) = \frac{AT}{A_r} r(t+1) \qquad (3.6)$$

In those equations $r(t)$ represents the setpoint changes and T is a scalar adjusted so as to preserve a unit gain for this reference model. The dynamics of the reference model are determined by the selection of the roots of the polynomial A_r.

Note that (3.5) is the desired closed loop reference ($r(t)$) to output ($y(t)$) transfer function, which is classical in conventional pole placement techniques, but that (3.6) is the corresponding closed loop reference to input transfer function which is usually not explicitly used but which plays a central rôle in the subsequent development. We now define deviations from the reference values by

$$\begin{aligned} \epsilon_y(t) &= A_f(y(t) - y_r(t)) \qquad (3.7) \\ \epsilon_u(t) &= A_f\Delta(u(t) - u_r(t)) \qquad (3.8) \end{aligned}$$

where A_f is a stable monic polynomial which will influence the regulation closed loop transfer function.

The classical model reference method, which in our case simplifies to a pole placement method since the reference model and the plant model have the same zeros, then amounts to finding the linear controller which sets $\epsilon_y(t)$ to zero (and simultaneously also sets $\epsilon_u(t)$ to zero), but this involves the solution of a sometimes numerically ill conditioned Diophantine equation. Instead of forcing $\epsilon_y(t)$ and $\epsilon_u(t)$ to be identically zero to achieve exact model matching, the way which will be followed here is to minimize the following criterion,

$$J(u,t) = \sum_{j=N_1}^{N_2} [\epsilon_y(t+j)]^2 + \lambda \sum_{j=1}^{N_u} [\epsilon_u(t+j-1)]^2\} \qquad (3.9)$$

$$\text{subject to } \epsilon_u(t+j) = 0, \quad j = N_u, \ldots, N_2.$$

Thus we have transposed a pole positioning aim into a GPC framework. When using (3.9) one will still apply a receding horizon strategy: N_u future control actions are defined by the optimization of the criterion but only the first one is actually applied at time t.

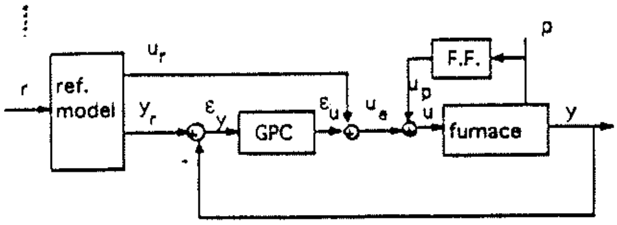

Figure 3.4: Controller structure for the 'performance model' GPC

In order to minimize (3.9) we need a model which relates $\epsilon_u(t)$ to $\epsilon_y(t)$ and which is called the 'performance model'. We shall first define the following quantity,

$$p_f(t) = Bu_p(t) + Pp(t) + K \qquad (3.10)$$

which is approximately zero when the load is steady, since it corresponds to the way the feedforward compensation is computed (see (3.3)). Then, it is an easy matter to show ([BGW90]) that the performance model is given by the following equation,

$$A\Delta\epsilon_y(t) = B\epsilon_u(t-1) + A_f\Delta p_f(t-1) + A_f\Delta e(t) \qquad (3.11)$$

From that model, and using diophantine equations which by now have become classical in GPC theory, predictions for $\epsilon_y(t+j)$ can be defined as follows,

$$A_f = AE_j + q^{-1-j}G_j \text{ with deg } E_j = j \qquad (3.12)$$

$$BE_j = A_f\Delta H_j + q^{-1-j}J_j \text{ with deg } H_j = j \qquad (3.13)$$

$$\epsilon_y(t+j+1) = \frac{G_j}{A_f}\epsilon_y(t) + \frac{J_j}{A_f\Delta}\epsilon_u(t-1) + A_fE_jp_f(t+j) + H_j\epsilon_u(t+j) \qquad (3.14)$$

In this last equation, and provided we make the assumption that the pull is going to remain steady or to be compensated appropriately by u_p (which amounts to supposing that $p_f(t+j) = 0, j > 0$), only the last term of the right hand side is unknown at time t.

As is standard in GPC theory, a vector of future predictions of $\epsilon_y(t+j)$ can be constructed and the minimization of the criterion with respect to the vector of future $\epsilon_u(t+j)$ is easily performed. The receding horizon strategy implies that only the first value, $\epsilon_u(t)$, is of interest to us, and from that value, using (3.8) and (3.6), the actual control $u_e(t)$ can be computed.

The control input $u_e(t)$ consists of a feedback term, which is based on the error between the output of the process and that of the reference model, and a feedforward term which is computed by this reference model. In addition to this comes the feedforward compensation of the pull $u_p(t)$. This is illustrated in Figure 3.4.

In order to meet industrial requirements, the final control structure also includes hard bounds on the control incremental variations $\Delta u_s(t)$, and $\Delta u_p(t)$ and on the total value $u(t)$.

3.3 Adaptation

The control algorithm described so far can be applied based on a fixed prediction model for the plant. However, several reasons pleaded in favour of an adaptive algorithm. Indeed, the operating conditions of the furnace may vary, and a typical example is the change of glass colour which has been illustrated in previous figures. When the glass colour changes, so do the process dynamics because heat transfer properties are different in white and coloured glass. Another reason is that the operators may have to change the amount of electrical heating, which also leads to a modification of the convection currents in the furnace and hence of the dynamics of the process. Finally, wear in the furnace over its life, and variations in the sensors are also motivations for the introduction of adaptation in the process model.

This has simply been done by combining an on-line recursive parameter estimation algorithm with forgetting of old data with the predictive control method just described, applying the certainty equivalence principle. Of course, this type of adaptive control algorithm is not without danger and safeguards on the estimation algorithm had to be installed in order to prevent the closed loop system from blowing up.

4 Industrial Results

In this section, we shall present and comment upon results which have been obtained on the real process. Of course, before installing the adaptive control algorithm on the process itself, many simulations had been performed in order to validate the approach. But the only validation which can eventually be trusted is when the real process sees its performance improved by using the above described control method. The control algorithm has been working on the furnace for nearly two years now, under the supervision of the operators and engineers of Glaverbel who are experts in glass making processes but certainly not experts in adaptive control.

Table 4.1 summarizes results during ten different periods of operation of the furnace, each of these periods representing several weeks. Standard deviations of the bottom temperature, σ_y, of the crown temperature, σ_u, and of the pull, σ_p, are given. The first five periods correspond to manual operation of the furnace while the GPC algorithm was controlling the bottom temperature during the last five periods. The results show an

type of control	$\sigma_y(^oC)$	$\sigma_u(^oC)$	σ_p
manual control	5.4	5.3	15.9
	6.8	6.5	18.2
	6.5	6.6	15.8
	8.6	7.9	16.9
	5.6	9.2	18.8
GPC control	2.0	7.9	14.3
	1.7	7.7	22.0
	3.7	7.4	14.8
	2.3	7.4	13.8
	2.7	7.7	17.5

Table 4.1: standard deviation of output, input and perturbation

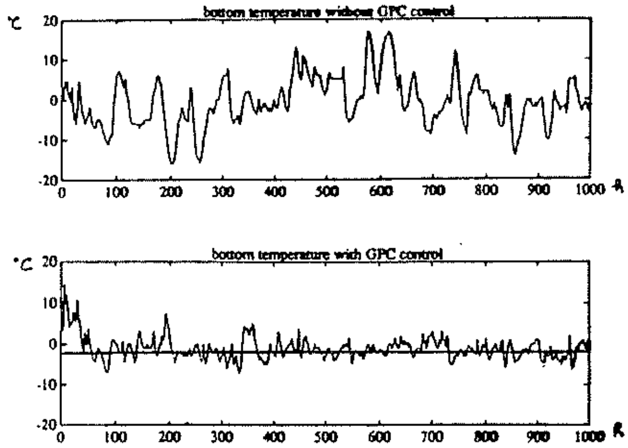

Figure 4.1: bottom temperature of the furnace without and with GPC

important decrease of the standard deviation of the bottom temperature without any significant increase in the standard deviation of the crown temperature, which is the control input. It has to be mentioned that one of the fears of the process engineers about this new control structure was precisely that the price to pay for better control of the bottom temperature would have been larger variations of the crown temperature, which then could have led to faster wear of the furnace. But this is not the case, as is also illustrated in the following figures which compare a period without GPC control algorithm to a period with GPC control. Figure 4.1 shows the bottom temperatures without and with GPC control and figure 4.2 illustrates the crown temperature variations under the same conditions.

Notice the improvement in the stability of this temperature. The setpoint given to the GPC controller was lower than the mean value of the bottom temperature under manual control, which explains the decrease of that temperature at the beginning of the controlled period. In fact, operators have been able to decrease the mean value of the bottom temperature by about ten degrees thanks to the introduction of the controller which reduces the bottom temperature variations. This repre-

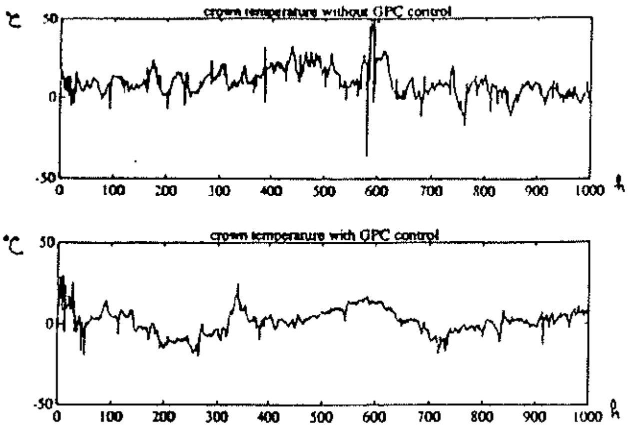

Figure 4.2: crown temperature of the furnace without and with GPC

sents valuable energy savings. Figure 4.2 shows that the crown temperature high frequency variations under GPC control are also reduced compared to manual operation.

There are indeed larger low frequency variations, but these are not harmful for the furnace, as long as the maximum value of the crown temperature stays below certain limits, which is ensured by the constraints we set on the control value in the algorithm.

5 Conclusions

This paper reported the application of adaptive predictive techniques to a real industrial environment, namely the control of the glass temperature in a glass furnace. This application has led to significant improvements in the furnace operation, and the best evidence of this is that similar algorithms are going to be installed on some other furnaces of the Glaverbel company. The predictive control structure based on a simple but still accurate prediction model of the bottom temperature certainly accounts for most of these improvements. One could question the necessity of adaptation in this structure, since the changes on the process which require adaptation (e.g. change of colour or change of electrical power) are known to the operator. Hence, a set of different parameter values for the prediction model and for the controller, corresponding to the various operating conditions, could possibly be stored and the controller would then switch from one parameter set to another according to the needs. This strategy is going to be explored on another furnace of the same company. Further research could also lead to the development of multivariable control structures. Finally, the first author would like to underline the innovative spirit of Glaverbel which allowed this research to run its proper course and find implementation on a practically important industrial process and not to have remained an academic (in the pejorative sense of the word) example.

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