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14th Triennial World Congress, Beijing, P.R. China

N-7a-10-1

APPLICATION OF A SIMPLE GPC WITH ROBUST BEHAVIOUR TO A SUGAR FACTORY

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Abstract: This paper presents the application of a Generalized Predictive Controller (GPC) to the diffusion process in a sugar factory. The controller was embedded in the existing control system, needing the same computational requirements as a PID routine. The control law is extremely simple to compute and the tuning is straightforward since a low order model is used. Due to model uncertainties that appear when working at different operating points, the original GPC algorithm is improved by the use of the so-called T polynomial, which increases the stability robustness by filtering the predictions. *Copyright © 1999 IFAC*

Keywords: Predictive control, Generalized predictive control, Robustness, Process control, Food processing.

1. INTRODUCTION

This paper shows an application of a GPC to a process in a sugar refinery. The implementation was carried out by the authors in collaboration with the firm PROCISA. The refinery is located in Peñafiel (Valladolid, Spain) and belongs to *Ebro Agrícolas*. The controller runs in a ORSI Integral Cube Control System, where the GPC has been included as a library routine which can be incorporated in a control system as easily as the built-in PID routine.

There are many applications of predictive control successfully in use at the present time (Qin and Badgwell, 1997), not only in the process industry but also applications to the control of a diversity of processes (Linkers and Mahfouf, 1994), (Richalet, 1993), (Richalet *et al.*, 1978). MPC is particularly attractive to staff with only a limited knowledge of control, because the concepts are very intuitive, and it can be used to control a great variety of processes, from those with relatively simple dynamics to other more complex ones.

The GPC method proposed by Clarke *et al.* (Clarke *et al.*, 1987a) is a reasonable representative of this family and has become one of the most popular MPC methods, being successfully implemented in many industrial applications (Clarke, 1988). As is well known, the basic idea of GPC is to calculate a sequence of future control signals in such a way that it minimizes a multistage cost function defined over a prediction horizon. The index to be optimized is the expectation of a quadratic function measuring the distance between the predicted system output and some predicted reference sequence over the horizon plus a quadratic function measuring the control effort. Generalized Predictive Control provides an explicit solution (in the absence of constraints), it can deal with unstable and non-minimum phase plants and incorporates the concept of control horizon as well as the consideration of weighting of control increments in the cost function. The general set of choices available for GPC leads to a greater variety of control objectives compared to other approaches, some of which can be considered as subsets or limiting cases of GPC.

A Generalized Predictive Controller results in a linear control law which is easy to implement once the controller parameters are known. The derivation of the GPC parameters requires, however, some mathematical complexities, which are difficult to solve in some industrial controllers. The industrial application of GPC in small control systems in industry has some difficulties that must be overcome. Apart from needing low computational requirements, it must be accepted by the plant operators. First, the tuning procedure must be simple enough, so that a GPC can be tuned as easily as a PID, and second, the controller must be robust, that is, it must behave well in the presence of the inevitable modelling errors.

The application shown here combines the power of predictive control with the simplicity and ease of use of the traditional controllers commonly found in industry. In order to improve the robustness of the closed loop system, the T polynomial has been added to the formulation.

The paper is organised as follows: Section 2 describes the application: the diffusion process in a sugar factory. The adaptation of the standard GPC algorithm to a wide class of industrial processes in order to reduce calculations and improve robustness is presented in section 3; section 4 is dedicated to the obtention of the plant model and section 5 to the presentation of operating results. Finally the conclusions of the work are presented in section 5.

2. THE DIFFUSION PROCESS

The factory produces sugar from sugar-beet by means of a series of processes such as precipitation, cristalization, etc. The process that is controlled in this application is the temperature control of the desummed juice in the diffusion.

In order to extract the sugar from the beet it is necessary to dilute the saccharose contained in the tuber tissue in water in order to form a juice from which sugar for consumption is obtained.

The juice is obtained in a process known as diffusion. Once the beet has been cut into pieces (called chunks) to increase the interchangeable surface, it enters into the macerator (which revolves at a velocity of 1 r.p.m.) where it is mixed with part of the juice coming from the diffusion process (see figure 1). Part of the juice inside the macerator is recirculated in order to be heated by means of steam and in this way it maintains the appropriate temperature for maceration. The juice from the maceration process passes into the diffusor (a slowly revolving pipe 25 m long and with a diameter of 6 m) where it is mixed with water and all the available sugar content is extracted, leaving

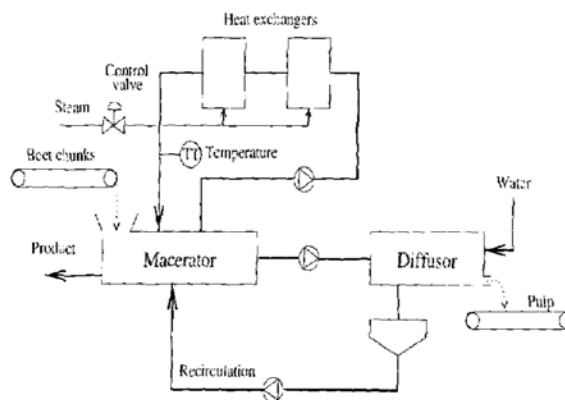


Fig. 1. Diffusion Process in a Sugar Refinery

the pulp as a sub-product. The juice coming out of the diffusor is recirculated to the macerator, from which the juice already prepared is extracted for the next process.

In order for the diffusor to work correctly it is necessary to supply thermal energy to the juice during maceration. In order to obtain this objective, part of the juice from the macerator (about $150 \text{ m}^3/\text{h}$) is made to recirculate through a battery of exchangers; within these the steam proceeding from the general services of the factory provides the heat needed to obtain optimum maceration. Therefore the controller must adjust the steam valve (u) in order to achieve a determined return temperature to the macerator (y).

The system response is seriously disturbed by changes in the steam pressure, which are frequent because the steam used in the exchangers has to be shared with other processes which can function in a non-continuous manner.

3. PRECOMPUTED GPC

This paper uses a formulation of Generalized Predictive Control (GPC), easy to implement and tune, that is valid for the majority of industrial processes (Camacho and Bordons, 1995), (Bordons and Camacho, 1998). The method makes use of the fact that a generalized predictive controller results in a control law that can be described with few parameters. The controller is valid for a wide class of processes in industry and a set of simple functions relating the controller parameters to the process parameters has been obtained. With this set of functions either a fixed or a selftuning GPC can be implemented in a straightforward manner.

Most processes in industry are high order systems that are not suitable for control purposes, but in general it is possible to approximate the behaviour of such high order processes with a simplified

model consisting of a first order process combined with a dead time element (Deshpande and Ash, 1981). This type of system is then described by the following transfer function:

$$G(s) = \frac{K}{1 + \tau s} e^{-s\tau_d} \quad (1)$$

where K is the process static gain, τ is the time constant or process lag, and τ_d is the dead time or delay. This model is widely used in industry to describe the dynamics of many processes, as shown by the popularity of the reaction curve method and the open loop Ziegler-Nichols PID tuning rules. Obviously better approximations could be obtained by using higher order models, but this would require identification packages which are not normally available in industry.

When the dead time τ_d is an integer multiple of the sampling time T ($\tau_d = dT$), the corresponding discrete transfer function of equation (1) has the form:

$$G(z^{-1}) = \frac{bz^{-1}}{1 - az^{-1}} z^{-d} \quad (2)$$

where discrete parameters a , b and d can easily be derived from the continuous parameters by discretization of the continuous transfer function, resulting in the following expressions:

$$a = e^{-\frac{\tau}{T}} \quad b = K(1 - a) \quad d = \frac{\tau_d}{T}$$

Therefore the CARIMA model used for the prediction is :

$$A(z^{-1})y(t) = B(z^{-1})u(t - 1) + \frac{C(z^{-1})}{\Delta} \xi(t) \quad (3)$$

where C is the noise polynomial. If it is chosen equal to one, the model results:

$$(1 - az^{-1})y(t) = bz^{-1}u(t - d) + \frac{1}{\Delta} \xi(t) \quad (4)$$

The predictions along the horizon from $t + d + 1$ to $t + d + N$ can be calculated by means of the following equation:

$$\hat{y}(t + d + j | t) = (1 + a)\hat{y}(t + d + j - 1 | t) - a\hat{y}(t + d + j - 2 | t) + b \Delta u(t + j - 1) \quad (5)$$

In (Bordons and Camacho, 1998) the GPC algorithm is derived for this kind of processes, leading to the control strategy shown in figure 2. The plant parameters are used to compute the controller coefficients (l_{y1} , l_{y2} , l_{r1}) as described in (Bordons and Camacho, 1998). These coefficients are precalculated as a function of the system pole (a) and the control weighting factor (λ) with horizons $N_1 = d + 1$, $N_2 = d + N$, $N_c = N$,

$N = 15$. The values $\hat{y}(t + d | t)$, $\hat{y}(t + d - 1 | t)$ are obtained by the use of the prediction which basically consists of a model of the plant which is projected towards the future with the values of past inputs and outputs and only requires straightforward computation. The control signal is divided by the process static gain in order to get a system with a unitary static gain. The control law is given by:

$$\Delta u(t) = l_{y1}\hat{y}(t + d | t) + l_{y2}\hat{y}(t + d - 1 | t) + l_{r1}r(t) \quad (6)$$

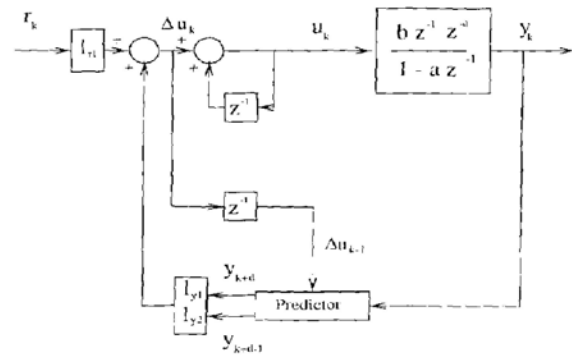


Fig. 2. Control Scheme

The control algorithm reduces to:

- 1 Compute k_{yi} as functions of the control weighting factor λ .
- 2 Make $l_{yi} = k_{1i} + k_{2i} \frac{\hat{a}}{k_{3i} - \hat{a}}$ for $i = 1, 2$ and $l_{r1} = -l_{y1} - l_{y2}$
- 3 Compute $\hat{y}(t + d | t)$ and $\hat{y}(t + d - 1 | t)$ using equation (5) recursively.
- 4 Compute control signal $u(t)$ with:

$$\Delta u(t) = l_{y1}\hat{y}(t + d | t) + l_{y2}\hat{y}(t + d - 1 | t) + l_{r1}r(t)$$
- 5 Divide the control signal by the static gain
- 6 Go to step 2.

It can be seen that the algorithm is really simple and can be easily included in any commercial control system without complex calculation requirements. This algorithm has been successfully tested in some experimental plants. However, it has also been shown (Camacho and Bordons, 1995) that although it is rather robust to gain and time constant uncertainties, it has small robustness to deadtime uncertainties, that are commonly found in real plants. That is why the algorithm must be modified to consider this circumstances, since the process to be controlled present that kind of uncertainty (as will be seen later).

The stability robustness of GPC can be improved with the use of an observer polynomial, the so-called $T(z^{-1})$ polynomial. In (Clarke and Mohtadi, 1989) a reformulation of the standard GPC algorithm including this polynomial can be found. In order to do this, the CARIMA model is expressed in the form:

$$A(z^{-1})y(t) = B(z^{-1})u(t-1) + \frac{T(z^{-1})}{\Delta}\xi(t) \quad (7)$$

Up to now the $T(z^{-1})$ has been considered equal to 1, describing the most common disturbances or as the colouring polynomial $C(z^{-1})$. But it can also be considered as a design parameter. In consequence the predictions will not be optimal but on the other hand robustness in the face of uncertainties can be achieved, in a similar interpretation as that used by Ljung (Ljung, 1987). Then this polynomial can be considered as a prefilter as well as an observer. The effective use of observers is known to play an essential role in the robust realization of predictive controllers (see (Clarke and Mohtadi, 1989) for the effect of prefiltering on robustness and (Yoon and Clarke, 1994) for guidelines for the selection of T).

This polynomial can be easily added to the proposed formulation, computing the prediction with the values of inputs and outputs filtered by $T(z^{-1})$. Then, the predictor works with $y^f(t) = \frac{y(t)}{T(z^{-1})}$ and $u^f(t) = \frac{u(t)}{T(z^{-1})}$. The actual prediction for the control law is computed as $\hat{y}(t+d) = T(z^{-1})\hat{y}^f(t+d)$.

The correct choice of the T polynomial is a problem that has not completely been solved, although its effect on the robustness of the closed loop system has been analysed in several papers (Clarke *et al.*, 1987b), (Clarke and Mohtadi, 1989), (Robinson and Clarke, 1991), (Yoon and Clarke, 1995). In this application, T is made equal to $A(z^{-1})(1 - \beta z^{-1})$, being β a value close to the system pole, as suggested in (Yoon and Clarke, 1995).

4. PLANT MODEL

The process is basically a thermal exchange between the steam and the juice in the pipes of the exchanger, with overdamped behaviour and delay associated to the transportation time of the juice through pipes about 200 meters long. These considerations, together with the observation of the development of the system in certain situations, justify the use of a first order model with delay.

A model was identified by its step response. Starting from the conditions of 82.42 °C and the valve at 57 %, the valve was closed to 37 % in order to observe the evolution; the new stationary state

is obtained at 78.61 °C. The values of gain, time constant and delay can easily be obtained from the response:

$$K = \frac{82.42 - 78.61}{57 - 37} = 0.1905 \frac{^{\circ}\text{C}}{\%}$$

$$\tau = 5 \text{ min} \quad \tau_d = 1 \text{ min } 45 \text{ s}$$

However, it is seen that the system reacts differently when heated to when cooled, the delay being quite a lot greater in the first case. A similar test changing the valve to 57 % again provides values of

$$K = 0.15 \quad \tau = 5 \text{ min } 20 \text{ s} \quad \tau_d = 4 \text{ min } 50 \text{ s}$$

Although an adaptive strategy could be used (with the consequent computational cost), a fixed parameter controller was employed, showing, at the same time, the robustness of the method when using the T -polynomial in presence of modelling errors. The error in the delay, which is the most dangerous, appears in this case. The following values of the model were chosen for this:

$$K = 0.18 \quad \tau = 300 \text{ s} \quad \tau_d = 190 \text{ s}$$

and sampling time of $T = 60 \text{ s}$.

It should be noticed that there are great variations in the delay (that produced on heating is about three times greater than that on cooling), due to which it is necessary to introduce the filter $T(z^{-1})$ in order to increase the robustness.

5. OPERATING RESULTS

With the nominal model chosen, the discrete parameters of the process model are given by:

$$a = 0.8187 \quad b = 0.0326 \quad d = 3$$

The controller coefficients can be computed (see (Bordons and Camacho, 1998)) calculating $k_{y_i}(\lambda)$ and then l_{y_1} , l_{y_2} and l_{r_1} as functions of the system pole in the form:

$$l_{y_i} = k_{1i} + k_{2i} \frac{a}{k_{3i} - a} \quad i = 1, 2$$

$$l_r = -l_{y_1} - l_{y_2} \quad (8)$$

$$k_{11} = -\exp(0.3598 - 0.9127\lambda + 0.3165\lambda^2)$$

$$k_{21} = -\exp(0.0875 - 1.2309\lambda + 0.5086\lambda^2)$$

$$k_{31} = 1.05$$

$$k_{12} = \exp(-1.7383 - 0.40403\lambda)$$

$$k_{22} = \exp(-0.32157 - 0.81926\lambda + 0.3109\lambda^2)$$

$$k_{32} = 1.045$$

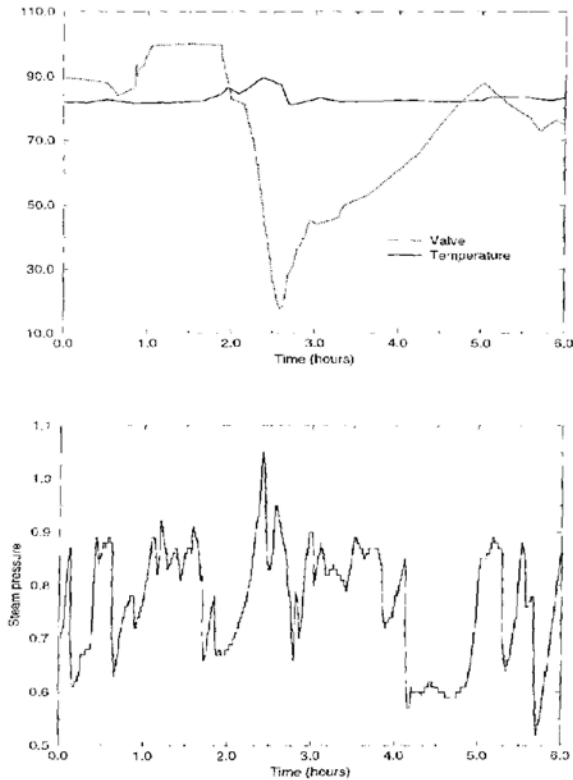


Fig. 3. System response in the presence of external disturbances

As the system pole is in 0.8187, if a value of λ equal to 0.2 is chosen, the controller coefficients are

$$l_{y1} = -4.2914 \quad l_{y2} = 2.4165 \quad l_{r1} = 1.8749$$

The following figures show various moments in operating the temperature control. The behaviour of the controller rejecting the disturbances (brusque variations in the steam pressure and load changes) can be seen in figure 3. On the other hand, figure 4 shows the response to a setpoint change in the juice temperature.

The controller interface allows the process parameters to be changed on line. The model is tuned by the operator as soon as a discrepancy between the actual and the predicted outputs (that appear on the screen) is detected.

Following many operational days the operators themselves concluded that a satisfactory model was given by:

$$K = 0.25 \quad \tau = 250 \text{ s} \quad \tau_d = 220 \text{ s}$$

with a control weighting factor $\lambda = 0.1$, a sampling time of 50 seconds and robust filter of $T(z^{-1}) = A(z^{-1})(1 - 0.8az^{-1})$, being a the discrete pole.

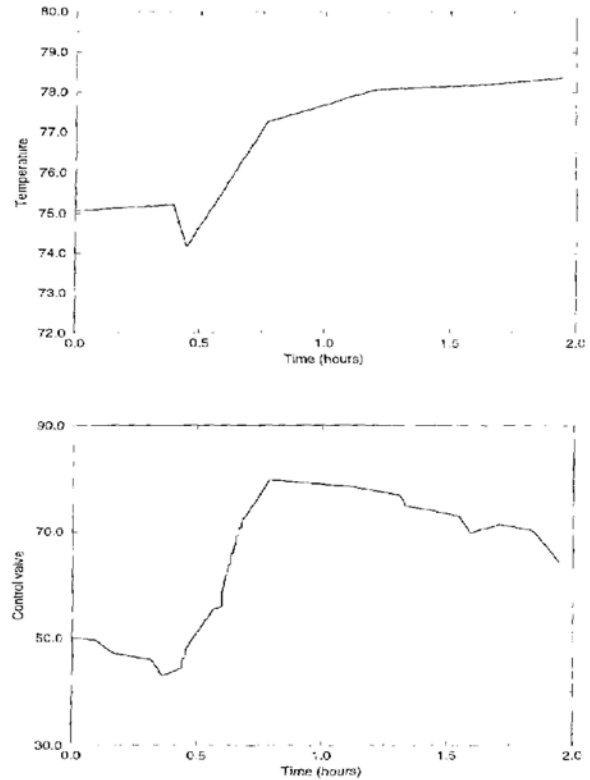


Fig. 4. Setpoint change

It should be emphasised that this controller worked satisfactorily and without interruption until the end of the year's campaign, being handled without difficulty by the plant operators. The results obtained using this controller in terms of error variance improved the ones obtained in the last year's campaign, when the process was controlled by a PI.

Notice that these results have not been compared to those of using the controller without the T polynomial. The reason for this is that removing the polynomial made the closed loop unstable (due to the big dead time uncertainty). As it is a real application, the filter had to be included in the controller when the output started to show a dangerous behaviour.

6. CONCLUSIONS

An application of a Generalized Predictive Controller (GPC) to the diffusion process in a sugar factory has been presented. The control law was extremely simple to compute and the tuning was straightforward because of the low order model used. The original GPC algorithm was improved by the use of the T polynomial to increase the stability robustness, since model uncertainties appeared when working at different operating points. The

controller has been successfully working in the factory, showing a good behaviour.

7. ACKNOWLEDGMENTS

The authors would like to acknowledge Juan Herida from PROCISA by his interest and support in the development of the controller and the people from Ebro Agrícolas by the facilities for testing the controller in the plant. The financial support of CICYT by projects TAP 96-0884 and TAP 98-0541 is gratefully appreciated.

8. REFERENCES

- Bordons, C. and E.F. Camacho (1998). Generalized Predictive Controller for a Wide Class of Industrial Process. *IEEE Transaction on Control Systems Technology* **6**(3), 372–387.
- Camacho, E.F. and C. Bordons (1995). *Model Predictive Control in the Process Industry*. Springer-Verlag.
- Clarke, D.W. (1988). Application of Generalized Predictive Control to Industrial Processes. *IEEE Control Systems Magazine* **122**, 49–55.
- Clarke, D.W. and C. Mohtadi (1989). Properties of Generalized Predictive Control. *Automatica* **25**(6), 859–875.
- Clarke, D.W., C. Mohtadi and P.S. Tuffs (1987a). Generalized Predictive Control. Part I. The Basic Algorithm. *Automatica* **23**(2), 137–148.
- Clarke, D.W., C. Mohtadi and P.S. Tuffs (1987b). Generalized Predictive Control. Part II. Extensions and Interpretations. *Automatica* **23**(2), 149–160.
- Deshpande, P.B. and R.H. Ash (1981). *Elements of Computer Process Control*. ISA.
- Linkers, D.A. and M. Mahfonf (1994). *Advances in Model-Based Predictive Control*. Chap. Generalized Predictive Control in Clinical Anaesthesia. Oxford University Press.
- Ijung, L. (1987). *System Identification. Theory for the user*. Prentice-Hall.
- Qiu, S.J. and T.A. Badgwell (1997). An Overview of Industrial Model Predictive Control Technology. In *Chemical Process Control: Assessment and New Directions for Research*. In: *AIChE Symposium Series 316, 93*. Jeffrey C. Kantor, Carlos E. Garcia and Brice Carnahan Eds. 233–256.
- Richalet, J. (1993). Industrial Applications of Model Based Predictive Control. *Automatica* **29**(5), 1251–1274.
- Richalet, J., A. Rault, J.L. Testud and J. Papon (1978). Model Predictive Heuristic Control: Application to Industrial Processes. *Automatica* **14**(2), 413–428.
- Robinson, B.D. and D.W. Clarke (1991). Robustness effects of a prefilter in Generalized Predictive Control. *Proceedings IEE, Part D* **138**, 2–8.
- Yoon, T.W. and D.W. Clarke (1994). *Advances in Model-Based Predictive Control*. Chap. Towards Robust Adaptive Predictive Control, pp. 402–414. Oxford University Press.
- Yoon, T.W. and D.W. Clarke (1995). Observer Design in Receding-Horizon Control. *International Journal of Control* **2**, 151–171.