APPLICATION OF MODEL PREDICTIVE CONTROL FOR QUALITY CONTROL OF GLASS MELTING PROCESSES

Ton Backx, Jobert Ludlage, Anton Koenraads
IPCOS Technology, Bosscheweg 145[a], 5282 WV Boxtel, The Netherlands

1. Introduction

In the past decade glass industries, like most process industries, have been confronted with a major change in the market. Competition is increased drastically and environmental legislation has been tightened severely. The strong growth in production capacity has exceeded the growth in market demand. This has resulted in a very competitive market that is largely customer controlled and that is showing saturation.

The market has developed from a *supplier driven* market to a *demand driven* market. In this market margins on products are eroding rapidly. Good margins can only be obtained for products that are scarce and have demand. Customer dictated markets are capricious. Opportunity windows for good margin product sales get shorter. This makes it necessary for producers to respond quickly and reliably to product demands. Products have to be delivered with short notice in strictly defined time windows at the right quality and in the requested volume.

These market changes enforce industries to flexibly produce small series of a large variety of changing product types with equipment that has a lifetime of 7-12 years. The innovative power to bring new products to the market quickly, in a predictable and controlled way, is becoming a necessity for industries to improve or even maintain their market position.

In order to prepare for these drastic changes, tight control of the production processes over a broad operating range is needed. Process operation has to enable a completely *predictable* and *reproducible* changeover to different operating conditions like load changes (tonnage), color changes and batch material composition changes.

This paper explaines how process models and model based control systems can be used to operate processes in the most flexible way, in accordance with market requirements and driving towards conditions that maximize margins. We will show how this technology can be used to push processes closer to their physical limits in order to obtain a better economic result.

2. Model Concepts

In general processes consist of various manufacturing steps. Detailed knowledge and understanding of process behavior in relation to each of these steps is the key to obtaining the intended improvements in process operation. Examples of such steps in glass manufacturing are: preparation of batch and batch transport, charging of batch material in the melter, melting and refining of glass, conditioning of the glass for further processing, manufacturing of the products, conditioning of the products, post-processing of the products. Each of these processing steps is performed in dedicated processing equipment or dedicated manufacturing installations. These processing units enable realization of the proper processing conditions for high performance manufacturing. The sub-processes that run in the installations have to fulfil certain requirements to ensure that the resulting products obey specifications. In each process

step a number of variables (e.g. residence time and residence time distribution, temperature profile in the melter or forehearth, hot spot temperature and its location, concentration, homogeneity and purity of batch components, concentration of undesired components, furnace pressure, exhaust gas oxygen excess, …) determine the course of the process and consequently the characteristics of the products produced. They have to be kept within the specified tolerance limits or have to be brought within these limits during a process change over, to guarantee good product quality and to ensure lifetime of the manufacturing equipment. These variables are called Controlled Variables (CV's).
In order to keep the CV's within the specified region, a number of process variables have to be moved within a predefined region within which they can be manipulated by the operator or a control system. These variables -the so-called process *inputs* or *MV's* (Manipulated Variables)- are used to compensate for external disturbances and for changes in the observed process behavior.
The third category of process variables are the so-called process *disturbances or DV's* (Disturbance Variables). Examples of these variables are e.g. impurities of the batch components, composition of the batch, humidity, ambient temperature, furnace wear, reversal of firing, Wobbe index, … . These variables determine the process behavior, just like the manipulated variables do. In contrast to the manipulated variables, Disturbance Variables cannot be manipulated. Consequently, we have to accept the presence and the resulting effects on the processing of these disturbances. In the best case disturbances that affect processing are measurable. Their ultimate effect on product properties or on the process may be predictable over a certain time horizon. In model based control terminology these measured disturbances are often refered to as *DV*'s (disturbance variables). Unmeasured disturbances are then considered to be part of the output noise. Figure 1 gives a general overview of a process and the variables defined above.

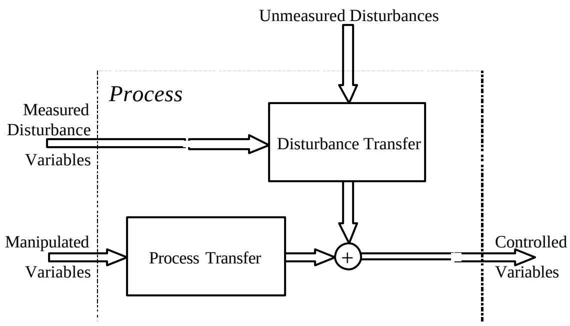

Fig. 1 General representation of a process and the defined variables

In general the process installations as well as the processes that run in the processing equipment exhibit inertia. When a variable is adjusted, e.g. a gas flow, the process starts changing and arrives, after the so-called response time, at a new steady state corresponding to a new operating point. This behavior, where the process changes over a characteristic time interval in response to a manipulation of a process variable or a change in a disturbance variable, is called the dynamic behavior of the process. A model can describe this dynamic process behavior over the relevant time interval. The step response is a well-known example of such a dynamic model. The step response is the response of process variables and product parameters on a unit step adjustment of a manipulated variable

The step response model is a specific model representation of the process dynamics. Other model types that represent dynamic behavior are impulse responses, transfer functions, Differential-Algebraic Equations (DAE's) and state space models.
Model based control systems explicitly use the knowledge of the dynamic behavior of the process, as described by the models, to determine the best possible control strategy under given market and production circumstances.

3. Model Predictive Control

Multivariable processes are processes whose inputs influence more than one process output simultaneously. Characteristic for Model Predictive Control (MPC) is that the control strategy can be adjusted for each calculation of a next control action. As a result MPC is very flexible for changing conditions, like e.g. changing requirements, switching-off or failure of sensors and actuators. Moreover MPC can deal with constraint type of requirements, i.e. it can keep both manipulated as well as controlled variables in certain pre-defined ranges. MPC has been developed within the industry, emerging from the need to operate processes tighter within operational and physical constraints of the process and applied equipment and closer to the operating constraints that maximize margins. From its initial development [RIC78, Cut80] MPC has grown to a widely proven technology in especially oil refining, that robustly pushes the controlled process to operating conditions that maximize margins and reduce process variability. In glass manufacturing the benefits mostly stem from tight control of product quality, increase of efficiency and minimization of energy consumption.
The success of MPC within industry is for a major part due to the fact that MPC meets industrial requirements. These requirements can be roughly divided into three groups:

- *Operational requirements*
  Processes have to be operated within a predefined region (Safety constraints, maximum load conditions of equipment, environmental load, wear, …)
- *Product Quality requirements*
  Products have to be produced at specifications (Cpk values, 6-sigma ranges, …).
- *Economic requirements*
  Products must be produced in such a way that margins are maximized, without violating operating constraints.

Figure 2 shows a block diagram of an MPC control system. Initially, MPC did not explicitly take constraints into consideration. Further refinements of the technology developed at the end of the eighties allow constraints on both input and output variables to be considered in the formulation of the control strategy. A paper of Qin en Badgewell [Qin96] gives a good overview of the MPC technology that is currently applied in industry.

MPC without constraints

The basic principle of MPC can best be illustrated on the situation without constraints. The finite impulse response (FIR) model, describing the dynamic behavior of a process with m inputs and p outputs, can be used to describe how input manipulations $u(t)$ applied to the process at discrete time instances in the past $t=k-i$, influence the process output $y(t)$ at the discrete time instance $t=k$:

$$y(k) = \sum_{i=1}^{N} M_i u(k-i) \qquad (1)$$

where the pxm matrix elements M_i are the so-called Markov parameters or Impulse Response elements. The model is a linear approximation of the relevant process dynamics in the selected operating point.
The future behavior of the process outputs is determined by both the input manipulations applied to the process in the past (*u(k-i) |i=1,2, …)* and the future input manipulations (*u(k+j) |j=0,1,2,…)*, if we assume k to be the current time instance.
By defining $Y_{fp}(t,N_f,N_p)$ as the influence that the past input manipulations over the horizon $[t-N_p,t-1]$ have on the future outputs over the time horizon $[t,t+N_f]$ at time instant t and by defining in addition $Y_{ff}(t,N_f,N_c)$ as the influence that future input manipulations over the time horizon $[t,t+N_c]$ have on the future outputs over the time horizon $[t,t+N_f]$, the predicted future behavior at the process outputs at time instant t over the time horizon $[t,t+N_f]$, say $Y_f(t,N_f)$, is determined by:

$$\begin{aligned} Y_f(t,N_f) &= Y_{fp}(t,N_f,N_p) + Y_{ff}(t,N_f,N_c) \\ &= H(N_f,N_p)U_p(t,N_p) + T(N_f,N_c)U_f(t,N_c) \end{aligned} \tag{2}$$

In this expression $H(N_f,N_p)$ is the so-called Hankel matrix; $T(N_f,N_c)$ is the so-called Toeplitz matrix. The three vectors, $Y_f(t,N_f) \in \Re^{(N_f p)x1}$, $U_p(t,N_p) \in \Re^{(N_p m)x1}$ and $U_f(t,N_c) \in \Re^{(N_C m)x1}$ are respectively the vector containing the predicted future process output responses $Y_f(t,N_f)$, the vector with past process input manipulations $U(t,N_p)$ and the vector with the future process input manipulations $U(t,N_c)$.
In MPC terminology the horizon t to $t+N_f-1$ is called the *prediction horizon.* The *control horizon* equals the time horizon t to $t+N_C-1$. The above distinction between the influence that past and future input manipulations have on the predicted future behavior of the process outputs is visualized in figure 3.
This distinction between the influence of the past and future input manipulations on the future outputs, respectively $Y_{fp}(t)$ en $Y_{ff}(t)$, is relevant for MPC since:

- *Past input manipulations have already been applied to the system and are therefore fixed.*
- *Futures input manipulations have not yet been applied to the process and are therefore still free to be chosen*

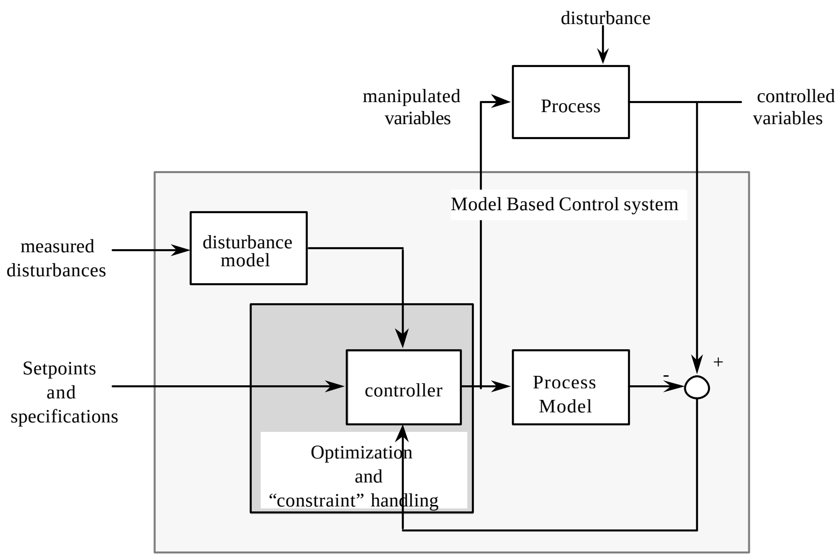

Fig. 2 Schematic representation of a model based process control system

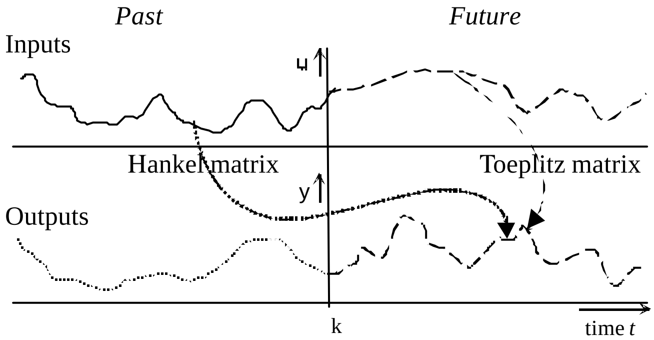

Fig. 3 Relation between the past and future process inputs and the future process outputs.

In MPC these future input manipulations, which are still to choose freely, are chosen such that the future behavior at the process outputs and inputs are as good as possible in accordance with the desired behavior of these process variables. Hence the future input manipulations are the degrees of freedom that can be used to optimize the process behavior. MPC uses a quadratic criterion function for this minimization of deviations of the desired process output responses:

$$\min_{U(t,N_C)} \left\{ \left\| W_{SP}(Y_{ref}(t,N_f) - Y_f(t,N_f)) \right\|_2^2 + \left\| r\Delta U(t,N_C) \right\|_2^2 \right\} \qquad (3)$$

with:

$$\Delta U(t,N_C) = \begin{bmatrix} u(t) \\ u(t+1) \\ u(t+2) \\ . \\ u(t+N_C-1) \end{bmatrix} - \begin{bmatrix} u(t-1) \\ u(t) \\ u(t+1) \\ . \\ u(t+N_C-2) \end{bmatrix} \qquad (4)$$

The above optimization problem is solved for each controller interval, since new information, i.e. new measurements from the process, become available to refine the solution. This is called the *receding horizon* principle of the controller. The input manipulations are determined over the complete control horizon. However, only the first sample of the calculated control solution *u(t)* is actually sent to the process. The expression W_{sp} is an output weight that enables the designer to define the distribution of the error between the desired output behavior $Y_{ref}(t,N_f)$ and the actually predicted process output behavior $Y_f(t,N_f)$ over the different outputs. In MPC the matrix W_{sp} generally is a diagonal matrix with a constant value per output. This value is frequently specified by its inverse: the so-called "*Equal Concern factor*". The move weight r is also a diagonal matrix and is specified by one parameter per input. This parameter is frequently called the *"Move Suppression factor"*. The move suppression factor is used to trade-off fast changes of the corresponding input against the other inputs and against the outputs.

MPC with constraints

An essential extension of MPC is the optimization with constraints. The inclusion of constraints gives the MPC the characteristics and flexibility desired by industry.

Constraints can be defined on process inputs, process outputs and additional variables whose relation with the process inputs can be described by a linear function:

$$\min_{U_f(t)} \left\{ \left\| W_{SP}(Y_{ref}(t) - Y_f(t)) \right\|_2^2 + \left\| r\Delta U_f(t) \right\|_2^2 \right\} \tag{5}$$

subject to:

$$\alpha_L(i) \le u(t+i) \le \alpha_U(i) \quad \text{for i=1, 2, 3, …}$$
$$g_L(i) \le \Delta u(t+i) \le g_U(i) \quad \text{for i=1, 2, 3, …}$$
$$b_L(i) \le y(t+i) \le b_U(i) \quad \text{for i=1, 2, 3, …}$$

In these expressions α_L, β_L, γ_L en α_U, β_U, γ_U respectively represent the lower- and upper limits defined on input variables, output variables and the rate of change in the input variables. The constraints not only give the control system its desired flexibility, but also enable the implementation of complex control strategies with control hierarchies.

4. An application of MPC in the glass industry

Typical applications of MPC in the glass industry are the control of crown-, glass- and bottom temperatures in a:

- melting furnace.
- refiner
- forehearth

for the production of TV panels/funnels as well as for the prodction of container and of float glass.

Especially a melting furnace has very slow dynamics, typically with response times of several hours upto a day. This is where model predictive control performs well, because it consistently updates and keeps track of all applied changes in heating/cooling adjustments, and the way they work out on all individual glass temperatures taking into consideration the full history of process manipulations over several shifts. Moreover, the process of glass melting is a highly interactive system with both spatial and temporal flow patterns that connect glas temperatures and the related glass processing conditions in a dynamic way. Every change in heating/cooling simultaneously affects almost all glass temperatures and therefore the processing conditions relevant for glass quality.
Finding an optimum for the operation of such a process is not a straightforward task.
In general there are three optimization criteria, that should be satisfied with decreasing priority:

1. *safety*: constraint demands to protect the construction and the equipment from damage
2. *quality*: control to meet product specifications and imposed environmental constraints
3. *economic optimization of operation*: maximize efficiency and minimize energy consumption

To protect the furnace from unacceptable control solutions (e.g. changing the heating/cooling too fast, damaging the construction), constraints on heating/cooling levels, crown temperature profile and -range are applied. This means that the MPC will never violate these safety constraints in order to satisfy a control objective of a lower priority: “Safety first !”

Most of the time the process is controlled in a safe operating region, with room to move the MV's for the purpose of keeping quality variables on target with minimum variability; despite the ever present disturbances, such as changing batch compositions and temperature disturbances.
A final optimization objective is minimization of the operating costs. In glass industry this mostly means: saving energy and maximizing efficiency. For each particular control interval, the "cheapest" solution is determined, that satisfies all constraints and quality requirements. The combined adjustments on all heating and cooling flows is additionally chosen to minimize costs. Especially for melting furnaces, which typically consume a lot of fuel, the potential for cost reduction is considerable in general.

Normally a refiner connects to a number of forehearths. These forehearths take care of the distribution of the glass melt to the forming equipment. Production problems or a product change-over on one forehearth can severely degrade the operation of the other forehearths in the form of (inlet) temperature disturbances. Applying MPC on the refiner can anticipate problems and minimize the disturbing effects. Furthermore, the individual MPC of each forehearth can compensate for the remaining disturbances, long before the effect is felt at the forehearth exit, where the forming process takes place.
Because normal forehearths use both heating and cooling, conflicting simultaneous adjustments of heating and cooling flows can be avoided, thus saving some energy, without giving up on quality control.

A control objective for MPC control on a forehearth in general is to drive glass temperature distribution on a vertical cross section near the bowl to a specified profile. The aim is to improve the temperature homogeneity conditions of the glass to an optimum for further processing.
Figure 4 shows a typical operator interface to an MPC controlled forehearth. Notice the graph, showing converging glass temperatures, after the MPC was switched on.
Fig 5 shows these converging temperatures in more detail.

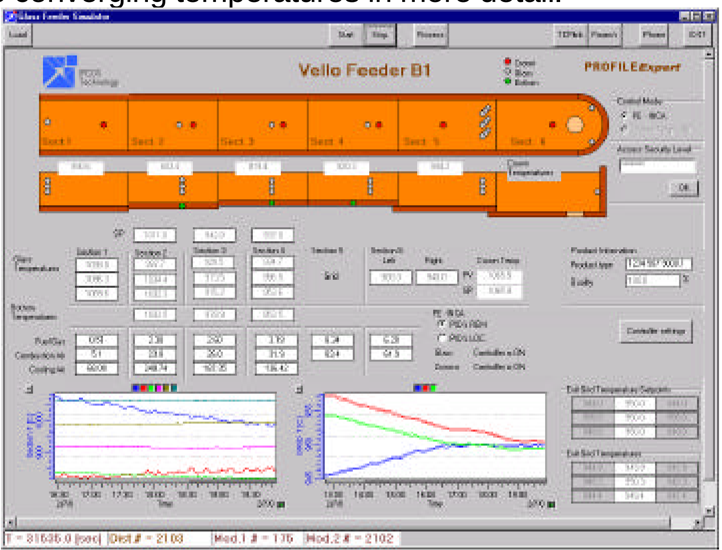

Fig. 4. A Model Predictive Controller, applied to control glass temperature homogeneity

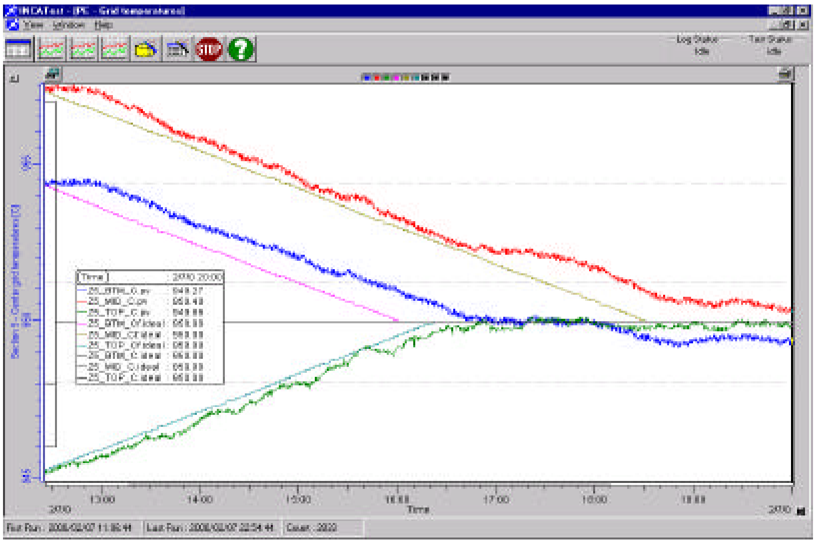

Fig. 5. Converging glass temperatures near the bowl (maximum homogeneity objective)

5. Concluding remarks

In this paper an overview has been given of model based control systems, which are more and more applied in process industry. The discussed MPC technology is widely applied in oil processing industries today and is an emerging new technology in glass manufacturing. The bottom line driver for applying this technology is its widely demonstrated capability to improve business performance. The break-even point of investments in applications of this technology is in general reached well within one year.
The power of the latest MPC technology is illustrated by a description of typical MPC applications in the glass industry. MPC can cope with safety, quality and economic demands in the proper context. The dense interaction matrix of a typical glass process, combined with its extreme slow dynamics make these applications ideally suited for application of MPC. Dedicated MPC based applications for a broad range of glass manufacturing processes are entering the market now.

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