Model-based glass melter control

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2.3.4 Conclusion and Outlook

From the above results, we can draw the following conclusions:

- From theoretical considerations it follows that the maximum heat-power input by eddy currents happens near the wall of the crucible, whereas at the axis of the cylinder (center of the crucible) the power input is zero.

- The simulations show that radiation and convective mass transport are responsible for the heat transport in the interior of the hot glass.

- Furthermore, the simulations show that the profile of the power input (strongly increasing from the center towards the wall of the crucible) is completely different from the resulting temperature field. Therefore, it is in general impossible to draw any conclusions from the temperature field with respect to the distribution of the power input!

- The material parameters for electrical conductivity, effective heat conductivity (as an approximated parameter for the radiation transport), and viscosity should be known up to the maximum temperature used; if not, these parameters must be extrapolated for very high temperatures. The latter two parameters control whether the heat transport in the melt is primarily due to radiation or convection.

The so-called skull crucible method can be applied to make glass melt “in its own juice”. Here, the wall of the crucible is actively cooled, whereas the temperature of the glass-melt interior is kept constant. To avoid cooling of the melt interior, power input and heat loss are balanced over an average time. For a 50-L crucible, an electric power of $\approx 70$ kW (without electric power losses) is necessary, which is instantaneously transferred to the cooling agent and to the surroundings as a power loss. An additional amount of energy is needed to heat up the glass from the starting temperature to a certain maximum temperature.

2.4 Model-Based Glass Melter Control

**Introduction**

Glass industries, like most other process industries, have been confronted with a major change in the market during the past decades. Competition has drastically increased and environmental legislation has been tightened severely. The strong growth in production capacity in general, and in container-glass manufacturing in particular, has exceeded the growth in market demand. This has resulted in a market that is largely customer-controlled and saturated. In addition, the complexity and costs of production equipment have significantly increased owing to the tightening legislation on ecosphere load, and operation of the processes within the ever-tightening constraints has become increasingly more complex as well.

One of the major reasons for the changes is globalization of the market. Globalization is one of the results of the recent developments in the fields of telecommunication, transportation, and advanced automation, which have emerged from the rapid developments in electronics and computer and information technology. As a consequence, the process industry is nowadays...
confronted with a strongly competitive market. The market has developed from a supplier-driven market to a demand-driven market. These changes have far-reaching consequences for producers. In this market, margins on products are eroding rapidly. Good margins can only be obtained for products that are scarce and in demand. Customer-dictated markets are capricious. Opportunity windows for good margin product sales are tightening. This requires producers to respond quickly and reliably to product demands. Products have to be delivered at short notice in strictly defined time windows in the right quality and the requested volume.

These market changes enforce industries to flexibly produce small series of a large variety of product types, preferably with existing production installations. A further consequence of these changes in the market is a continuous shortening of the life cycle of a significant part of supplied product types. 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 operation at and changeover between different operating points that correspond with the production of various product types under different economic objectives (minimize costs, maximize production rate, minimize stock, benefit from fluctuating prices, etc.). The strategy yielding the most profitable conditions has to be selected from a variety of potential operating scenarios to produce the desired product type. This decision is based on a thorough understanding of both process behavior and process operation. The freedom of choice offered in process operation must be used to predictably produce precisely what is required in terms of quality, volume, and time, with the best achievable business result.

This section explains how process models and model-based control systems can be used to support process operation in the most flexible way, in accordance with market requirements and driving towards conditions that maximize margins. The use of model-predictive control technology to push processes closer to their physical limits in order to obtain a better economic result is discussed. Because the performance of model-based process control systems relates one-to-one to the accuracy of the models applied, we start with a short introduction into modeling and model concepts.

2.4.1 Model Concepts

Detailed knowledge of process behavior and extensive use of this knowledge are the key for obtaining the intended improvements in process operation. Mathematical models are the vehicles for making knowledge on process behavior accessible for automated process operation.

Glass-manufacturing processes consist of a sequence of manufacturing steps. In each of these production steps, specific processing conditions need to be realized to guarantee ultimate product quality. The main steps are:

- preparation of batch and batch transport,
- charging of batch material in the melter,
- melting and fining 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 needs to satisfy particular specifications. The available operating envelopes of the processing units enable realization of the specified processing conditions for high-performance manufacturing, if they are appropriately designed. In each process step, a number of variables determine the course of the process and consequently the characteristics of the resulting products (e.g., component separation, residence time and residence-time distribution, temperature profile in the melter or forehearth, hot-spot temperature, hot-spot location, boosting, bubbling, concentration, homogeneity and purity of batch components, concentration of undesired components, glass level, furnace pressure, exhaust gas oxygen excess, NOx, temperature distribution in forehearth cross-section, etc.). A selection of critical processing variables and a number of product properties of the semi-manufactured and final products have to be kept within specified tolerance limits or have to be brought within these limits during a process changeover to guarantee good ultimate product quality and to ensure high lifetime of the manufacturing equipment. These process variables are the so-called process outputs or CVs (controlled variables).

In order to keep the CVs in their predefined region, a set of process variables are available for manipulation of the process behavior. These variables have a predefined operating region within which they can be manipulated by the operator or the control system. These variables, the so-called process inputs or MVs (manipulated variables) are used to compensate for external disturbances and changes in the observed process behavior. They have to drive the process to the desired operating conditions along preferred paths.

The third category of process variables that affect the process behavior are the so-called process disturbances or DVs (disturbance variables). Examples of these variables are impurities of the batch components, composition of the batch, humidity of the batch and the combustion air, ambient temperature, furnace wear, reversal of firing, Wobble index, and so on. These variables determine the process behavior in a manner similar to the MVs, but unlike them, DVs cannot be manipulated. Consequently, we have to accept the presence of these disturbances and the resulting effects on the processing. In the best case, the disturbances affecting 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 referred to as DVs. Unmeasured disturbances are then considered to be part of the process output noise. Figure 2.42 gives a graphical representation of a process and the variables defined above.

As an example, a melting tank can be used. The most relevant variables for control of a melting tank are:

- **Controlled variables (CVs)**
  - glass level
  - batch composition
  - batch position
  - hot-spot temperature
  - glass temperature profile

- **Manipulated variables (MVs)**
  - total fuel flow
  - fuel-flow distribution
  - air/fuel or oxygen/air/fuel ratio for each burner
  - cooling air

- **Disturbance variables (DVs)**
  - batch composition (unmeasured disturbance)
  - batch humidity (measured or unmeasured disturbance)
  - ambient temperature (measured or unmeasured disturbance)
  - draught (unmeasured disturbance)
  - furnace wear (unmeasured disturbance)
  - foaming (unmeasured or measured disturbance)
  - Wobbe index or fuel composition (measured or unmeasured disturbance)

In general, the process installations as well as the processes running in the processing equipment exhibit inertia. When a variable is adjusted, for example a gas flow, the process starts changing for a while. After the so-called response time, it arrives at a new steady state that corresponds to a new operating point. This dynamic 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 dynamic process model can describe the relevant dynamic process behavior for the complete transition 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.

Figure 2.43 gives an example. The step response in this figure shows how the underlying process changes due to a step change at the input; it characterizes the changeover from one operating point as a function of time to another operating point. Detailed analysis of the response in Fig. 2.43 shows that the process output, after a short delay time of approximately 2 min, initially moves in the wrong direction for about 15 min, after which the output reaches its final value in around 80 min.

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 (DAEs), and state space models. Each model type has its specific mathematical representation. Process models can, within certain limits, be used for simulation and prediction of the expected process responses on arbitrary input signals applied to manipulated variables and/or disturbance variables of the process. Consequently, these models enable the prediction of the process outputs in the near future on the basis of known adjustments on the manipulated variables and known behavior of the measured disturbance variables in the recent past. The process models can also be used to determine which manipulated variable adjustments are to be applied to the process in order to bring it efficiently...
to a desired state, i.e., in accordance with the business goals. The bottom line is: Models make process behavior more predictable, controllable, and optimizable. 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. In the design of classical PID control systems the model is only implicitly applied for determination of the controller P, I, and D parameters.

### 2.4.2 Model-Predictive Control

A model-predictive control (MPC) system is an ideal tool for control of multivariable processes. Multivariable processes are processes whose inputs influence more than just one process output simultaneously. Characteristic for MPC is that the control strategy can be adjusted for each calculation of a following control action. As a result, MPC is very flexible for changing conditions such as, for example, changing requirements, switching-off or failure of sensors and actuators. Moreover, MPC can deal with constraint-type requirements, i.e., it can keep both manipulated as well as, to some extent, controlled variables in certain predefined 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 [2.162, 164], MPC has grown to a widely proven technology, especially in oil refining. The dominant use of MPC in oil-refining applications implies robustly pushing the controlled process to operating conditions that maximize margins and minimize process variability. Formost refinery applications, this results in maximization of the throughput of a certain product mix. In glass manufacturing, the benefits mostly stem from tight control of product quality, increase of average furnace load, increase of efficiency, tight control of emissions and minimization of energy consumption.

The success of MPC within industry is to a large extent due to the fact that MPC meets industrial requirements. These requirements can be roughly categorized into three groups.

- **Operational requirements:** processes have to be operated within a predefined region (safety, emissions, wear, etc.).
- **Product-quality requirements:** products have to be produced at specifications (C_p values, 6-sigma ranges, etc.).
- **Economic requirements:** products must be produced in such a way that margins are maximized, without violating operating constraints.

Figure 2.44 shows a block diagram of an MPC control system. Initially, MPC did not explicitly take constraints into consideration. Refinements of the technology developed at the end of the 1980s allow constraints on both input and output variables to be considered in the formulation of the control strategy. A paper by Qin and Badgwell [2.165] 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 demonstrate 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 current discrete time instance $t = k$:

$$y(k) = \sum_{i=0}^{N} M_{i} u(k - i) .$$

where the $p \times m$ matrix elements $M_{i}$ are the so-called finite impulse response (FIR) parameters or Markov parameters.

Figure 2.45 shows the way the FIR model of the process is applied for constructing the prediction of the process outputs. The input signal $u(t)$ is decomposed into a sequence of time-shifted "impulses" that compose the original process input after summation. The bars with length $a_{i}$ represent the impulses with amplitude $a_{i}$ that enter the process. They are the input signal samples resulting from sampling of the continuous process input signals. The process output signals $y_{i}$ result from summation of all elements at row $i$ of the impulse response elements scaled by the sample amplitude of the corresponding input signal sample.
2. Melting and Fining

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The FIR model can be used to describe the process output $y(t)$ at discrete time instances $t = k - i$ in the past. More interestingly, when the input manipulations $u(t)$ at the discrete time instances in the future $t = k + i$ are known, the model can also be used to describe the evolution of the process output $y(k + i)$ at discrete time instances in the future:

$$
\begin{bmatrix}
y(k)
y(k+1)
y(k+2)
y(k+3)
y(k+4)
\end{bmatrix}
= M_0 \begin{bmatrix}
y(k-1)
y(k-2)
y(k-3)
y(k-4)
y(k-5)
\end{bmatrix}
+ \cdots
+ M_{i-1} \begin{bmatrix}
y(k-i)
y(k-i+1)
y(k-i+2)
y(k-i+3)
y(k-i+4)
\end{bmatrix}
+ \cdots
(2.135)
$$

The future behavior of the process outputs is therefore determined by both the input manipulations applied to the process in the past $(u(k - i))_{i=1}^{\infty}$ and the future input manipulations $(u(k + j))_{j=0}^{\infty}$.

By defining $Y_p(t, N_f, N_p)$ 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 $Y_f(t, N_f, N_p)$ as the influence that future input manipulations over the time horizon $[t, t + N_f]$ 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 $Y(t, N_f)$, is determined by

$$
Y(t, N_f) = Y_p(t, N_f, N_p) + Y_f(t, N_f, N_p)
= H(N_f, N_p) U(t, N_p) + T(N_f, N_p) U_f(t, N_f),
$$

where $H(N_f, N_p)$ is the so-called Hankel matrix:

$$
H(N_f, N_p) = \begin{bmatrix}
M_{N_f} & \cdots & M_1 & M_0 & 0 & \cdots & 0 \\
M_{N_f+1} & \cdots & M_2 & M_1 & M_0 & \cdots & 0 \\
\vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\
M_{N_f+N_p-1} & \cdots & M_{N_f-2} & M_{N_f-3} & M_{N_f-4} & \cdots & M_0 \\
0 & \cdots & 0 & \cdots & 0 & \cdots & 1
\end{bmatrix}
$$

This Hankel matrix is the tool that enables prediction of future process output responses on the basis of known past process input signals.

$T(N_f, N_p)$ is the so-called Toeplitz matrix:

$$
T(N_f, N_p) = \begin{bmatrix}
M_0 & 0 & \cdots & 0 \\
M_1 & M_0 & \cdots & 0 \\
M_2 & M_1 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
M_{N_f-1} & M_{N_f-2} & \cdots & M_0 \\
M_{N_f} & M_{N_f-1} & \cdots & M_1 \\
0 & \cdots & \cdots & \cdots & 1
\end{bmatrix}
$$

This Toeplitz matrix is the tool that enables prediction of future process output responses to future process input manipulations.

Three vectors, the vector containing the predicted future process output responses, $Y_f(t, N_f) \in \mathbb{R}^{[N_f] \times 1}$, the vector with past process input manipulations, $U(t, N_p) \in \mathbb{R}^{[N_p] \times 1}$, and the vector with the future process input manipulations, $U_f(t, N_f) \in \mathbb{R}^{[N_f] \times 1}$, are defined as

$$
Y_f(t, N_f) = \begin{bmatrix}
y(t)
y(t+1)
y(t+N_p-2)
y(t+N_p-1)
\end{bmatrix}, \quad
U(t, N_p) = \begin{bmatrix}
u(t)
u(t+1)
u(t-2)
u(t-1)
\end{bmatrix}
$$

and

$$
U(t, N_f) = \begin{bmatrix}
u(t)
u(t+1)
u(t+N_p-2)
u(t+N_p-1)
\end{bmatrix}.
$$

(2.139)
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 influences of past and future input manipulations on the predicted future behavior of the process outputs is visualized in Fig. 2.46.

The distinction between the influence of the past and future input manipulations on the future outputs, respectively \( Y_p(t) \) and \( Y_f(t) \), is relevant for MPC because:

- past input manipulations have already been applied to the system and are therefore fixed;
- future input manipulations have not yet been applied to the process and are therefore still free to be chosen.

In MPC, these future input manipulations are chosen such that the future behavior at both the process outputs and process inputs is close to the desired behavior of these process variables. Hence the future input manipulations are the degrees of freedom that can be used to optimize the future process behavior. MPC uses a quadratic criterion function for the minimization of deviations of the desired process output responses:

\[
\min_{u(t,N_c)} \left\{ \| W_{pp}(Y_{ppt}(t,N_f) - Y_p(t,N_c)) \|^2 + \| u \Delta U(t,N_c) \|^2 \right\}
\]

(2.140)

with

\[
\Delta U(t,N_c) = \begin{bmatrix}
  u(t) \\
  u(t+1) \\
  u(t+2) \\
  \vdots \\
  u(t + N_c - 1)
\end{bmatrix} = \begin{bmatrix}
  u(t-1) \\
  u(t) \\
  u(t+1) \\
  \vdots \\
  u(t + N_c - 2)
\end{bmatrix}
\]

(2.141)

The above optimization problem is solved for each controller interval because new information, i.e., new measurements from the process, becomes 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 vector \( u(t) \) is actually sent to the process. The matrix \( W_{pp} \) is an output weight that enables the control system designer to define the distribution of the error between the desired output behavior \( Y_{ppt}(t,N_f) \) and the actually predicted future process output behavior \( Y_p(t,N_c) \) over the different outputs. In MPC, the matrix \( W_{pp} \) 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 \( p \) 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.

Observe the dominant role that the process model plays in the above formulation of the control problem. It is clear that the attainable performance of the controller is closely related to the quality of the applied process models: Accurate models enable high-performance control.

In the prediction of the future output behavior it is easily possible to include disturbance models, i.e., models describing the relation between measured disturbances and the process outputs. Including the effect of these disturbances on the future output behavior the optimization criterion enables the optimization to account for these effects during the calculation of the future input moves. In fact, this is a feed-forward control action, i.e., the controller already starts compensating for the disturbance before it actually becomes visible at the process output. This resembles the behavior of a person who retracts when someone tries to hit him/her. Retracting minimizes the pain of the offense. The incorporation of disturbance models in the controller may drastically improve the controller performance: instead of waiting for the negative effects of the disturbance to become fully visible at the process outputs, they are anticipated already on the basis of predictions of process outputs. But note that, because the model predicts the effect of the measured disturbance at the output, the actual improvement is completely determined by the quality of the predictions of the disturbance model.

MPC with Constraints

An essential extension of MPC with respect to the MPC described in the previous section, is the optimization with constraints. The inclusion of constraints gives the MPC the characteristies 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 some linear function:

\[
\text{Fig. 2.46. Relation between the past and future process inputs and the future process outputs}
\]
min \{ ||W_p(Y_{set}(t) - Y(t))||_2^2 + ||\Delta U(t)||_2^2 \} \quad (2.142)

subject to
\alpha_i(t) \leq u(t + i) \leq \alpha_i(t)
\gamma_i(t) \leq \Delta u(t + i) \leq \gamma_i(t)
\beta_i(t) \leq y(t + i) \leq \beta_i(t)

\text{for } i = 1, 2, 3, \ldots

Expressions \alpha_i, \beta_i, \gamma_i, \text{ and } \alpha_i, \beta_i, \gamma_i \text{ represent the respective 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, as discussed in the introduction to this section. Constraints are, for example, frequently used to define the operational requirements, i.e., the operational envelope within which the process may be operated. Note that constraints in general will limit the attainable performance of the process as soon as they become active. This is due to the fact that each active constraint implies loss of a degree of freedom in process operation. Constraints usually originate from safety limits and operating limits related to equipment constraints, which take priority over fulfilling the criterion function. The criterion function usually represents process performance considerations. The process performance directly relates to process economics.}

### 2.4.3 Extensions of the MPC Technology

The generation of MPC systems widely applied to oil-refining processes has a number of limitations that restrict broad industrial applicability. On the one hand, the restrictions are caused by the way the criterion function is minimized. On the other hand, the models applied in most of these MPC systems have severe limitations.

The first restriction is related to the fact that the solution of the criterion function, subject to constraints over the complete future horizon at each subsequent sampling instant, still requires significant computational power. The actual optimization problem is therefore in general approximated by a simplified problem requiring less computer power. A generally applied approach is to split the original formulation into two sub-problems: a steady-state problem and a dynamic problem, which is successively solved. The steady-state problem rigorously defines an optimal solution that fulfills all constraints and minimizes the criterion function at steady-state conditions. The solution for the input and output variables obtained from the steady-state optimization is then used as a target for the dynamic optimization. The dynamic optimization defines the path that brings the process variables from their current values to these steady-state targets. In particular, the rigorous implementation of the optimization of the dynamic control problem is computationally demanding. A number of simplifications are applied especially in this step.

These simplifications may significantly deteriorate the dynamic performance of the controller.

Another limit to the performance stems from the models applied in these MPC systems and the identification techniques used to determine these models. Nowadays, the most frequently applied types are

- finite step response (FSR) models,
- finite impulse response (FIR) models,
- low-order transfer function (TF) models, and
- low-order state space (SS) models.

These models are obtained from dedicated identification tests applied to the process. In general they describe only the part of the process dynamics that is relevant for control. The low-frequency behavior, i.e., the slow process responses and the steady-state process behavior, is well described by these models. The restricted validity of the dynamic model is directly determined by the identification techniques used. The fact that the models do not accurately describe the faster process dynamics relevant for control can have a direct impact on the performance of the MPC. The restricted validity of the dynamic model limits the MPC operation to a reduction of the variance of the slow variations of the process outputs only. The controller cannot compensate for the faster variations of the process outputs.

The quality improvement of critical product properties to be obtained with the current MPC generation is therefore restricted. This is important for problems where quality control, i.e., control of the so-called Cpk value of specified product and process parameters is an important objective (see Fig. 2.47).

![Fig. 2.47. Optimization of the "capability" (Cpk) of important process variables and product parameters using model-predictive control](image)
strict the application field of MPC technology. Current process identification techniques almost always result in linear dynamic models. Sometimes simple static, nonlinear functions at the inputs and outputs are applied to approximately describe nonlinear process behavior. This type of MPC systems is therefore restricted in its ability to control fast changeover between different operating points of the process and batch processes.

Hybrid models, i.e., models obtained from the integration of first-principle-based process models (e.g., CFD-based simulation models of melters, refiners, and forehearth) and models obtained with process identification techniques, are applied in the latest MPC systems. Hybrid models can not only increase the accuracy of predictions, they may also drastically reduce the costs associated with the modeling phase.

The latest generation of MPC systems copes with the above-discussed problems. These systems enable operation of processes closer to their physico-chemical operating limits. In this way, the problems posed in the introduction regarding the requirements on flexibility, predictability, and complete reproducibility of process operations in conformity with defined specifications become solvable.

2.4.4 Application of MPC in the Glass Industry

A typical application of MPC in the glass industry is the control of crown, glass, and bottom temperatures in melters, refiners, and forehearth.

Melters have particularly slow dynamics, typically with response times of several hours up to one day. This is where model-predictive control performs very well. 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 glass 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. The desired temperature profiles are adjusted in such a way that the average residence time and the residence-time distribution together with the time-temperature history of each small volume of glass meet specifications that link to product 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 and crown-temperature profiles and ranges 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 MVs for the purpose of keeping quality variables on target with minimum variability – despite ever-present disturbances, such as changing batch compositions and temperature disturbances.

A final optimization objective is minimization of the operating costs. In the glass industry, this mostly means saving energy, maximizing throughput at a given quality level, and maximizing efficiency. For each particular control interval, the “cheapest” solution satisfying all constraints and quality requirements is determined. The combined adjustments on all heating and cooling flows is additionally chosen to minimize costs. In particular 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 forehearth for the distribution of the glass melt to the forming equipment (e.g., a press for TV panels/funnels, containers and equipment for drawing tubes). Production problems or product changeover on one forehearth can severely degrade the operation of the other forehearth 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 foreheath use both heating and cooling, conflicting simultaneous adjustments of heating and cooling flows can be avoided, thus saving some energy, without degrading quality control.

Figure 2.48 shows the dynamic interaction matrix of a typical forehearth, exhibiting the step responses from each CV to each MV and the corresponding gains. As can be seen, almost all CVs are simultaneously influenced by almost all MVs. This is called the “multivariable” character of the process.

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 or gobbler to a specified profile. The aim is to improve the temperature-distribution conditions of the glass to an optimum profile for further processing.

Figure 2.49 shows a typical operator interface to an MPC-controlled forehearth (ProfileExpert®). Notice the graph, showing converging glass temperatures, after the MPC was switched on.
2. Melting and Fining

Fig. 2.48. The multivariable character of a typical forehearth model applied in a model-predictive control system

Fig. 2.49. Model-predictive controller applied to control glass-temperature homogeneity

Fig. 2.50. Converging glass temperatures near the bowl (objective: maximum homogeneity)

Figure 2.50 shows these converging temperatures in more detail. Figure 2.51 shows a comparison of the behavior of model prediction versus the actual behavior of one of the controlled temperatures. The actual temperature changes match the prediction very closely.

An example of an industrial application of the model-predictive control system is the control of a forehearth of a TV-panel production line intended to stabilize temperature profiles and to minimize gob-weight variations.

Fig. 2.51. Actual past and model-predicted future temperature during transition control
Figure 2.52 shows a comparison between the performance of a traditionally controlled process and the results obtained with the model-predictive control system under similar conditions.

**Conclusion and Outlook**

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. An extension of this proven technology that is optimized for control of glass-manufacturing processes 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.

Dedicated product development based on the MPC technology is ongoing to extend its applicability to a larger range of processes. The latest developments of the MPC technology in this respect are:

- robust high-performance control of molten, refiners and forehearts. These control systems stabilize temperature profiles at conditions that result in a significant reduction of the variance of critical product parameters and process variables. This enables production at desired Cpk values for specified product quality parameters thus maximizing the margins on the products;
- control of changeovers from one operating point to another along a trajectory in a completely predictable and reproducible way (maximum flexibility with regard to color, pull, or product-type changes);
- realization of control systems that provide a good balance between development and maintenance costs on the one hand, and profitability on the other hand.

The power of the latest MPC technology has been 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. It is ideally suited for application to typical glass processes with their dense interaction matrices and extremely slow dynamics. MPC technology is currently rapidly developing. Dedicated MPC-based applications for a broad range of glass-manufacturing processes are just entering the market.

**References**


2.52 R. Conradt, P. Suwannathada, P. Pimkhaokham: Local temperature distribution in the vicinity of an electrode, in Proc. 16th Symp. Int. on Combustion (The Combustion Institute, Pittsburgh, PA 1999) pp. 100—107


2.78 M. Cabe, M.A. Chaudhry: “Volatilisation from sodium-lime-silica melts at one atmosphere and reduced pressure”, Glass Technol. 16(6), 125-134 (1975).


2.141 P. Schill: "Batch melting in mathematical simulation of glass furnaces", in Proc. 3rd Int. Seminar on Mathematical Simulation in Glass Melting (Glass Service Ltd., Vsetin, Czech Republic 1999) pp. 97-100.


2.147 J. Wang, S. Brewster, B.W. Webb, M.G. McQuay, K. Bhatia: "A coupled combustion space/batch/melt tank model for an industrial float glass furnace", in Proc. 5th Int. Seminar on Mathematical Simulation in Glass Melting (Glass Service Ltd., Vsetin, Czech Republic 1999) pp. 84-95.


2.149 R.O.S. Prasad, A. Mikhopolov, A. Dutt: "Implementation of a glass batch melting model in the general purpose three-dimensional CFD code Fluent", in Proc. 5th Int. Seminar on Mathematical Simulation in Glass Melting (Glass Service Ltd., Vsetin, Czech Republic 1999) pp. 43-51.


2.153 E. Otser, S. Lepret, S. Lelandais: "Image processing for glass industry", in QUEV'90 Int. Conf. on Quality Control by Artificial Vision (Takeahara, Kagawa, Japan 1998).


3. Homogenizing and Conditioning

3.1 The Intensity of Mixing Processes

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Introduction

Tracer particles in high-viscosity fluids, such as polymer or glass melts, exhibit complex kinematics during mixing processes. At first glance, this is surprising because high viscosities are usually associated with "simple" flows. Nevertheless, a more thorough analysis shows that deterministic chaos is at work and that this is synonymous with good mixing.

The purpose of this work is to present feasible mathematical methods for a realistic assessment and improvement of the mixing effect of stirrers in glass melts. This is important because platinum stirrer systems are very expensive, and if they do not guarantee the desired homogeneity, the economic consequences for the production are serious. Of course, the same methods can also be applied for the analysis of the mixing effect of melting and refining tanks.

Predicting the homogeneity of glass melts quantitatively after the mixing process is difficult if all parameters of influence, such as diffusion and chemical reactions, are taken into account. However, statements about the absolute mixing quality are not necessarily required in practical process development. It is usually more important to improve and standardize already existing stirrers, and this can be achieved by comparing the mixing intensity of different types of stirrers. In this chapter, we only discuss the most fundamental mixing mechanism, namely the mechanically induced increase of the interfacial area between striae and basic glass, which is called mixing in the narrow sense.

3.1.1 Description and Quantification of Mixing Processes

The description and evaluation of the homogenization of glass melts is a complex problem. In this introductory section, we will precisely define the task and give an outline of a feasible working strategy.

The following considerations introduce the matter very briefly. They are far from being complete. The purpose is simply to make the state-of-the-art