OVERVIEW OF AUTOMATIC CONTROL OF GLASS FURNACES

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This survey presents the current state of art in the field of modeling, identification and control of processes in glass industry from the automatic control perspective. First, a brief characteristic and some specific issues concerning modeling and control task in glass manufacturing are given. Then approaches to finding a suitable model for purposes of controller design and its verification by means of computer simulation are described. Among these belong frequently used empirical modeling techniques (linear black-box models), fuzzy rules based models and reduced models built from first principles. This is followed by a survey of control strategies including manual and PID control, fuzzy control and model-based predictive control (MPC) together with some used or suggested control hierarchies and architectures. Advantages and drawbacks of each method are discussed. The paper is concluded by current challenges in automatic control of glass manufacturing processes.

INTRODUCTION

Glass manufacturing clearly represents a challenge for an automation engineer as it is a very complex process with complicated, nonlinear and sometimes not completely understood dynamical behavior. So it is still common that furnaces are controlled by simple controllers such as PID regulators or by manual interventions of furnace operators. As a result, the process may be kept in suboptimal conditions and acting disturbances may not be effectively rejected. However, market competition creates a need for tighter control of the process towards optimum, i.e. to maximize performance while minimizing the cost, energy consumption and emissions at the same time. Thus, advanced control strategies should be applied.

Variables relevant for control

Backx et al. [1] give a survey of the usual variables that have to be considered in modeling and control of glass furnaces. Process variables (or controlled variables) are the ones that should follow their desired values, usually specified by a production engineer:
– Crown temperature profile
– Glass and/or bottom temperature profile
– Glass melt level
– Exhaust gas composition (e.g. NOx)
– Position of the batch blanket
– Residence time distribution
– Furnace pressure

Manipulated variables represent inputs of the process that can be handled by the control system:
– Gas flows to the burners
– Air-to-fuel ratios for traditionally operated furnaces or (air and) oxygen-to-fuel ratios for oxy-fuel fired or oxy-fuel boosted furnaces
– Cooling air flows
– Batch charger speeds
– Bubbling flow
– Boosting power applied to various groups of electrodes

Naturally, the system is influenced by various disturbances among which typically belong:
– Measured disturbances - ambient temperature, cullet ratio, humidity of the batch, batch composition, pull rate
– Unmeasured disturbances - leaks, pollution of batch, false air, furnace wear

Characteristics of modeling and control tasks

In order to design and test a controller a suitable process model has to be found. It should describe all relevant process dynamics (impact of manipulated variables and measured disturbances on controlled variables) with sufficient accuracy and computer simulations of such a model should run much faster than the real time.

Basically, two types of control tasks occur in glass manufacturing, each requiring a different approach [2]:
– Keep all process variables (glass temperatures etc.) within a narrow operating range and compensate early enough for disturbances (batch contamination, fuel quality variations, air leakage etc.)
– Bring the process from one operating range to another in the best possible way (automate color or gob weight change etc.)

In accomplishing the control task also the following requirements should be satisfied

– Keep all crown and sidewall temperatures within a specified zone to lower the material damaging, avoid condensation etc.
– Keep the speed of the temperature changes in the melting tank below a certain limit to avoid thermal stress in the equipment

APPROACHES TO MODELING AND SIMULATION

Figure 1 depicts current modeling and control approaches together with their interactions. Two main modeling techniques are currently applied for modeling of glass manufacturing processes:

– Empirical modeling techniques, which model process behavior on the basis of observed process responses to applied test signals using process identification techniques (black-box models)
– First-principles-based modeling utilizing computational fluid dynamics (CFD) techniques (mathematical models) and reduced-order models derived from these CFD models

Empirical modeling techniques

Identification of linear black-box models is a common and general approach that was successfully applied in glass industry [3]. This technique is able to "learn" and simulate the process behavior just from data, no further description is necessary.

Parameters of these models have to be determined from data measured on a real process. Drawbacks of this method are time-consuming and hence expensive experiments on site (due to very slow furnace dynamics). Also, magnitude of input signal must be carefully chosen not to spoil production whereas, in the same time, it is necessary to get output readings above the noise level. Due to the changes of process properties in time (e.g. because of furnace aging) adaptive estimation of model parameters is often applied.

The resulting types of models are suitable for most linear controllers design and verification. However, they have quite severe limitations - as most glass processes have nonlinear behavior validity of the models is limited to the narrow operating range around the steady-state point they were identified at. Thus, they can fail in cases when, e.g., pull rate or glass color is changed or significant change in glass temperature occurs. A possible remedy to this is to have a set of models and switch between them in different operating modes.

Mathematical models

CFD models

Computational fluid dynamics (CFD) solvers based on first-principles are well established tools in glass industry. Depending on the fineness of the used grid for discretization of the partial differential equations describing the process, the model of, e.g., a melter is typically described by tens of thousands equations. Hence, computation takes a long time and simulators run only at a speed comparable to a real time. Also, a lot

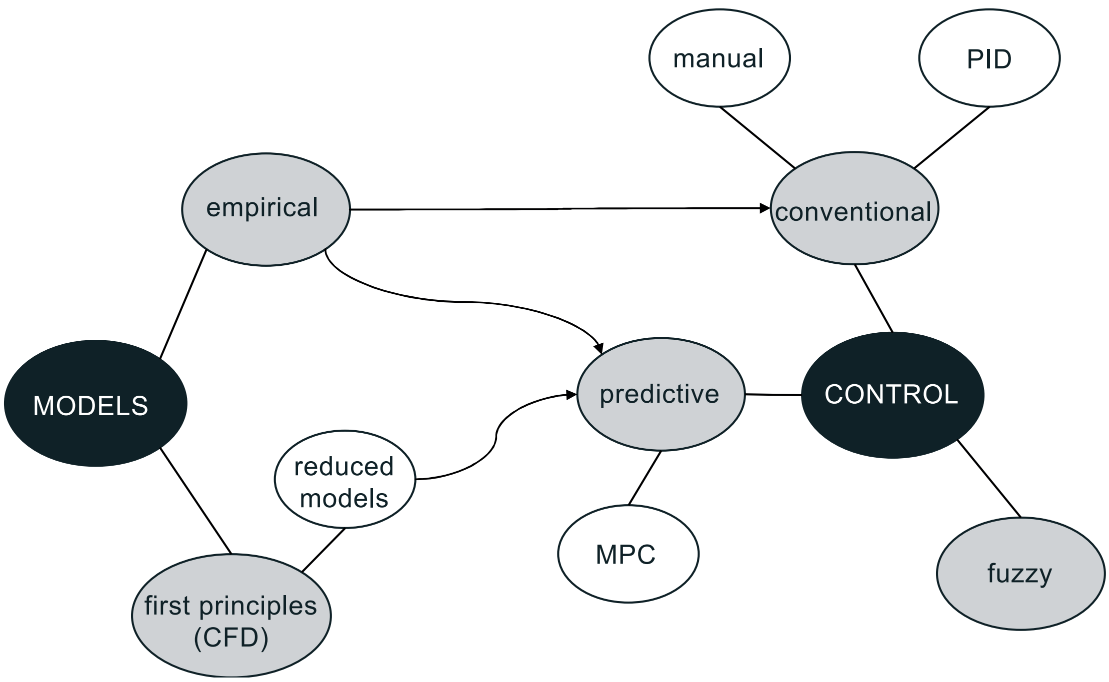

Figure 1. Modeling and control approaches.

of parameters, initial and boundary conditions have to be specified prior the simulation. Mostly for the speed reason the full-order CFD models are inappropriate for control design purposes.

Reduced-order models derived from CFD models

Models of lower order suitable for control design and verification can be obtained from existing CFD models by applying model reduction techniques. Basically, with a help of data generated from the full CFD model only the dominant behavior of the model is captured and hence number of equations can be significantly lowered. Research in this field is still going on but this method allows the controller design with lower engineering effort, in particular, dedicated testing and identification on site can be reduced significantly.

Astrid and Weiland [4] applied the reduction method to a CFD model of a glass feeder. In this technique, step tests are applied on the full-order CFD model and the acquired data is used to set up the low-order model via the proper orthogonal decomposition (POD) method. The original CFD model of a feeder described by 3 800 differential equations was reduced to a non-linear model only with 18 equations, resulting in significantly increased simulation speed. Due to larger input signals applied this model is able to describe the process dynamics in much wider range of operating points than on-site identified black-box model, e.g. for different pull-rates or glass color. However, this ability is influenced by the choice of input signals. Obviously, accuracy of such a model is dependent on the accuracy of the original CFD model.

Müller et al. [5] mention the need for calibration of the CFD model so that it sufficiently simulates the real furnace. With the validated model they use black-box identification to obtain linear models suitable for the MPC controller. On contrary to [4], a separate model is identified for each pull-rate in the feeder. Also an economical aspect of this modeling approach is mentioned - unless a glass manufacturer has a CFD model at his disposal at the point of control design, relatively high additional expenses must be spent to build the CFD model first.

Moreover, low-order models like the one developed in [4] are able to simulate the entire temperature distribution within the glass melt (with a certain level of accuracy), so they can also act as "soft-sensors", i.e. they can supply temperature readings to the controller even in places where there is no thermocouple in reality, and improve the performance of controller and quality of the glass.

APPROACHES TO CONTROL

Manual and PID control

Today significant part of process control in glass manufacturing is based on PID controllers and manual interventions of operators. This strategy faces its limitations in a lot of typical process situations because of multiple reasons. Some of them are listed below ([5, 6]):

– PID's are only SISO (single-input single-output) controllers. A PID controller is able to control only one process variable (e.g. a gas flow) by manipulating one actuator (e.g. a valve). Unfortunately, in glass industry the most interesting process variables are highly linked to each other (heating, cooling, ...).
– PID's have great problems to control plants with long dead times. In fact, long dead times can only be handled by conservative and careful PID settings which lead to bad control performance. Quite often this problem is overcome by controlling not the real interesting process variables like glass and bottom temperatures but controlling secondary variables like atmosphere temperatures.
– Typically product and load changes are done by manual interventions of the operators. This leads to different and sometimes quite long transitions.
– A real process operation optimization, depending on the actual process conditions, is also done manually by the operators. However, the glass production process is highly complex, nonlinear and multidimensional which makes this task for a human extremely difficult up to not solvable.

Model-based predictive control

Another concept overcoming some of the main drawbacks of manual and PID control is predictive control, which utilizes a model of the process for finding future optimal control actions. It can be clearly observed from published papers and rising amount of industrial applications that model-based predictive control (MPC) is a distinct current trend in glass manufacturing control.

There are several reasons explaining this trend and popularity of MPC control [7]. MPC control system is naturally suitable for controlling multi-variable processes and it can deal with constraint type of requirements, that is, it can keep both manipulated as well as process variables in certain predefined ranges. As MPC concept incorporates optimization it can cope with the control challenges in a straightforward fashion. In general, there are three optimization criteria that should be satisfied (with decreasing priority):

– *Safety:* constraint demands to protect the construction and the equipment from damage
– *Quality:* control to meet product specifications and imposed environmental constraints
– *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 their rates of change are applied. This means that the MPC should never violate these safety constraints in order to satisfy a control objective of a lower priority. Most of the time the process is controlled in a safe operating region, with room to move the manipulated variables for the purpose of keeping process 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. Especially for melting furnaces the potential for cost reduction is considerable in general.

Production problems or product changeovers on one forehearth can severely degrade the operation of the other forehearths in the form of temperature disturbances. MPC as a predictive control concept can anticipate these problems and minimize the disturbing effects long before they are felt at the forehearth or feeder exit, where the forming process takes place. A multivariable nature also allows to avoid conflicting simultaneous adjustments of heating and cooling flows.

Latest MPC concepts applied in a glass industry seem to be commercially successful; hence only little information on details of their implementations is revealed or published. Generally, MPC controller is strongly dependent on quality of the model used for prediction, mismatch of the model and real process may deteriorate its performance. Most of the reported industrial applications known to the author utilize only a simple linear model identified on-site for which MPC controllers have been well-established and used throughout industry. As it was mentioned in the section on mathematical models a new trend in the MPC control of glass manufacturing is to utilize low-order models obtained from CFD models. Some industrial applications for control of feeders are given in [5] and [8]. In the latter, a single reduced-order model is incorporated in a MPC controller that generates set-points for PID controllers in combustion zones of a feeder. The controller was successfully tested on an industrial emerald-green container glass feeder where product and pull-rate changes are frequent.

Fuzzy control

Since a significant part of glass manufacturing process is still manually controlled based on an experience of a human operator, rules embedded in proposed fuzzy controllers attempt to mimic the operator's behavior. This approach is able to cope with dead-times, changeable dynamics of the process, disturbances and uncertainty in model. Often, such a fuzzy controller is used for determining a set point for a lower-level control loop. Moon and Lee [9] presented an industrial application of fuzzy control on a TV glass furnace where originally both bottom and crown temperature was under manual control. Since the crown temperature can be easily modeled by a simple black-box model obtained from identification they devised a PI controller for this part. The set-point of the controller is given by a fuzzy controller with bottom glass temperature error and its change as inputs and change in crown temperature set-point as an output. Fuzzy rules were obtained from experience of furnace operators.

CONTROL SYSTEM ARCHITECTURES

Due to the complexity of a glass manufacturing process hierarchical and distributed control systems can find their place here. Usually, an upper-level system performs some optimizations and generates set points for the lower-level execution control loops.

A three-level hierarchical expert system is suggested in [10]. The lower level should include data acquisition, conventional control (PID's) and advanced control (MPC, fuzzy logic, neural networks). This level takes care of gas and air flow and glass level. The intermediate (supervisory) level should contain process monitoring, fault diagnoses, optimization, and supervisory control (set-point generation). It ensures optimum operating conditions (glass quality, thermal efficiency, low emissions...). The higher level makes strategic decisions, production planning and scheduling (glass type, fuel type, pull changes etc.)

A supervisory expert system could possibly compile and analyze real-time data, CFD simulations, operator observations and laboratory analyses to draw inferences and to issue recommendations for optimal operating of glass making process. The expert system can be either used on-line or off-line. In the on-line mode it gives recommendations, which specify the best control strategy to follow in predefined situations, to the operator. In the off-line mode the expert system can be used for training of new or inexperienced operators.

CONCLUSIONS

Despite the fact that automatic control of glass manufacturing process has evolved in the last twenty years, mostly thanks to rising capabilities of computers, still there is a lot to improve. Nowadays, mainly temperature control is applied in glass-melting furnaces partially due to a lack of sensors that would detect the important product parameters. Measurement of O_2, CO, SO_x and NO_x is occasionally available but is not often used for direct control. Anticipation and rejection of changes of redox state is desirable as well. Control task is also complicated by limitations in the degrees of freedom offered by the available actuators to manipulate the process which causes that not all disturbances can be compensated for [1].

Model predictive control is likely to become widespread in the glass industry in future and less and less on-line process optimization will be left upon human operators. One of the key issues is how to obtain models utilized in the controller as well as for simulation purposes. Certainly, research of reduced-order models derived from the CDF models will continue and hopefully bring further results. It also turns out that rather than a linear model a non-linear one should be employed in order to better describe behavior of the process in a wide operating range, especially in some applications, like E-glass melts for fiber production [11]. Such a model could be then used both for open-loop simulations (e.g. for showing effects of operator's intervention) and closed-loop simulation (for controller design and testing).

Consequently, currently used model-based predictive control concepts based on a linear model could be substituted by a nonlinear model predictive control to achieve better performance. However, this is not an easy task and still a lot of research is going on in this area (e.g. [12] provides an overview).

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PŘEHLED AUTOMATICKÉHO ŘÍZENÍ SKLÁŘSKÝCH PECÍ

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Tento přehledový článek představuje současný stav modelování, identifikace a řízení procesů ve sklářském průmyslu z pohledu automatického řízení. Nejprve je podána stručná charakteristika úlohy a vyjmenovány specifické problémy při automatickém řízení výroby skla. Poté jsou popsány možné přístupy pro nalezení modelu procesu, který je vhodný pro návrh a testování regulátorů pomocí počítačové simulace. Mezi ně patří často používané empirické metody tvorby modelu (lineární modely typu „black-box"), modelování pomocí fuzzy pravidel a redukce řádu matematických modelů. Následuje přehled používaných strategií řízení zahrnujících PID regulátory, fuzzy řízení a prediktivní řízení založené na modelu (MPC) spolu s několika používanými nebo navrhovanými hierarchickými strukturami automatického řízení. U každé metody jsou diskutovány její výhody a nevýhody. Závěrem článek poukazuje na současné otevřené otázky v této oblasti.