

Modeling and control methods for thermal regimes in the bending of automotive glass

Tokhirjon Musurmonov
Omadjon Urishev
Fergana State Technical University

Abstract: *This paper reviews the scientific literature on modeling and control of thermal regimes in the gravity bending (sagging) of automotive windshields. Existing approaches are classified into three groups: physics-based (numerical) models, simplified and data-driven models, and furnace temperature control methods. The groups are compared in terms of accuracy, computational speed, data requirements and the feasibility of implementation on industrial programmable logic controllers (PLCs). In addition, a lumped thermal model and a simplified viscous-flow estimate are used to show that, during an unplanned stoppage, glass in the bending zone reaches the zone temperature within 1-2 minutes, and that the permissible stoppage time depends quadratically on glass thickness and inversely on the fourth power of the windshield length. The analysis shows that most studies address the normal operating mode, whereas control of the bending process under abnormal conditions, such as unplanned stoppages, remains insufficiently studied. Directions for future research are proposed.*

Keywords: *automotive glass, windshield bending, heating furnace, thermal regime, mathematical modeling, automatic control, machine learning, abnormal operating mode*

1. INTRODUCTION

Requirements for automotive glass are constantly increasing in modern automotive engineering: glazing shapes are becoming more complex, their dimensions are growing, and requirements for optical quality and geometric accuracy are becoming stricter. The production of a laminated windshield consists of several interrelated stages: cutting, edge processing, ceramic paint printing, bending, lamination and autoclave treatment [1]. A defect that appears at any stage propagates to the subsequent stages; therefore, a systematic approach to quality management is required [1].

Bending is one of the most complex stages of automotive glass production. The correct geometry of a windshield depends on the condition of the molds, the temperature regimes and the proper grouping of glass on the furnace carriages. At the same time, an improper change of the regime may adversely affect the other glass sheets already in the furnace [1]. Conduction, convection and radiation in a semitransparent medium occur simultaneously during bending, which complicates both modeling and control of the process [2].

There are many scientific works on modeling and control of the bending process; however, they have been carried out in different fields - heat transfer, materials science, data analysis and automatic control theory - and remain largely disconnected. From the standpoint of process automation, it is a relevant task to systematize these approaches, to assess their applicability in production and to identify open problems.

The aim of this paper is to analyze and classify the methods of modeling and control of thermal regimes in the bending of automotive glass and to evaluate them from the standpoint of their application in automation systems.

2. LITERATURE REVIEW AND TECHNICAL BACKGROUND

2.1. Physics-based models of the bending process

Physics-based models rely on the numerical solution of differential equations describing heat transfer and glass deformation.

G. Buonanno et al. developed a three-dimensional thermal model of naturally ventilated ovens used in windshield production [4]. Convection, conduction and radiation were taken into account by the finite volume method, and the temperature distribution in the glass was validated against the data of a specially built experimental apparatus. According to the authors, such a model makes it possible to ensure the required product characteristics in advance, without iterative tuning.

M. Parsa et al. simulated windshield bending in two commercial finite element programs assuming viscoplastic behavior of soda-lime glass and coupled one of them with an optimization program to control the glass surface temperature [5]. The results showed that thermal stresses must be considered for accurate simulation, while higher forming temperatures may reduce production time. The simulation results were compared with the measured slope and thickness of formed glass sheets.

Q.-L. Zhang et al. simulated hot bend-forming using a simplified three-dimensional model of a windshield, mold and rings and compared the results with three groups of product samples in terms of bending depth and rebound rate [6]. A. Wang et al. studied a windshield heating furnace in ANSYS Workbench, examined the influence of specific heat, thermal expansion coefficient and radiation coefficient of glass on forming accuracy, and proposed an optimized furnace structure [7].

Radiation modeling is a particular challenge in physics-based models. B. Le Corre et al. compared different thermal models in glass sagging simulation and showed that neglecting radiative transfer leads to large errors in the temperature distribution and final shape [8]. At the same time, simplified approaches, such as the Rosseland approximation or a predefined glass temperature, gave acceptable results with slightly lower accuracy but much shorter computation time. F. Béchet et al. described the entire forming and tempering process with a two-dimensional finite element model including internal radiative effects [9].

In general, physics-based models provide detailed information on the thermal and mechanical state of the process and are useful for furnace design and preliminary recipe preparation. However, they require detailed temperature-dependent material properties, specialized software and large computational resources, which makes their direct use in real-time control systems difficult.

2.2. Simplified and data-driven models

The second group includes models that describe the relationship between process inputs and outputs on the basis of production or experimental data. They are simpler and faster than physics-based models and can therefore be used directly in control systems.

A series of works by R.I. Makarov and co-authors is devoted to the bending of laminated windshields. Random inspection of manufactured products revealed deviations of the surface tensile stresses at the glass edge from the specifications, and adaptive models describing the dependence of these stresses on the sag bending temperature were built [10]. On this basis, a bending temperature control algorithm was developed, and simulation showed that the stresses can be stabilized. A later work proposed a logistic regression model determining the probability of obtaining a high-quality product as a function of the bending regime [11]. According to the authors, such a model is effective for on-line inspection and for decisions on bending regime adjustment. Another work built linear regression models relating the sagging depth to the bending temperature and showed by simulation that the corresponding control algorithm improves product quality [12].

The general form of such models is as follows. A linear regression model describing the dependence of bending depth on the bending zone temperature [12]:

$$w = a_0 + a_1 \cdot T_b + \varepsilon_w, \quad (1)$$

where w is the bending depth, mm; T_b is the bending zone temperature; a_0, a_1 are coefficients determined by the least squares method from production data; ε_w is the model error. A logistic regression model estimating the probability of a high-quality product [11]:

$$P(Y = 1 | \mathbf{x}) = \frac{1}{1 + \exp\left(-(b_0 + \sum_{i=1}^m b_i \cdot x_i)\right)}, \quad (2)$$

where $Y = 1$ denotes a high-quality product; $\mathbf{x} = (x_1, \dots, x_m)$ is the vector of bending regime parameters; $b_0, \dots, b_m$ are model coefficients. Model (2) is directly converted into a decision rule: if P falls below a threshold, the bending regime must be adjusted.

A. Khoudi et al. compared several machine learning models (linear, Ridge and Lasso regression, and gradient boosting) for predicting the quality of automotive tempered glass from heating and quenching parameters [13]. The Ridge regression model gave the best result. An important feature of this work is that the model was implemented as a device connected to the production process: if the predicted quality does not meet the requirements, the device sends a signal back to the machine. Thus, the authors proposed a methodology from idea to industrial deployment.

The Ridge regression model determines the coefficients by minimizing the following functional:

$$\hat{\boldsymbol{\beta}} = \operatorname{argmin}_{\boldsymbol{\beta}} \left[\sum_{j=1}^N (y_j - \mathbf{x}_j^T \cdot \boldsymbol{\beta})^2 + \lambda \cdot \sum_{i=1}^m \beta_i^2 \right], \quad (3)$$

where y_j is the quality index of the j -th product; $\mathbf{x}_j$ is the corresponding vector of process parameters; N is the number of observations; λ is the regularization parameter. Increasing λ shrinks the coefficients and improves the stability of the model on production data with many correlated parameters.

The combination of physics-based and data-driven approaches is also developing. K.-I. Chang et al. applied surrogate models trained on finite element simulation results to a glass forming process and evaluated their robustness to temperature measurement uncertainty [14]. Such an approach bridges accurate but slow physics-based models and fast practical models.

The advantages of this group are simplicity, speed and the use of data already available in production. Its drawbacks are that a model is reliable only within the range of training data, sufficient high-quality data are required, and the results of complex machine learning models are difficult to interpret physically.

2.3. Furnace temperature control methods

A wide range of approaches, from classical controllers to artificial intelligence methods, has been proposed for temperature control in glass production furnaces.

U.-C. Moon and K. Y. Lee applied a hybrid approach to temperature control of a glass melting furnace for TV picture tubes [15]. The linear part of the furnace dynamics was described by a first-order-plus-dead-time (FOPDT) model with a proportional-integral (PI) controller, while the complex nonlinear part was covered by a fuzzy system based on the rules of experienced operators. Both parts were combined in cascade, and the system was implemented in an industrial company. This work demonstrates the practical effectiveness of combining a simple model with expert rules.

The transfer function of the FOPDT model and the PI control law are:

$$W(s) = \frac{K \cdot e^{-\tau s}}{T_p s + 1}, \quad (4)$$

$$u(t) = K_p \cdot e(t) + K_i \int_0^t e(\xi) d\xi, \quad (5)$$

where K is the process gain; τ is the dead time; T_p is the time constant; $e(t)$ is the difference between the setpoint and measured temperature; K_p , K_i are the proportional and integral gains. The parameters of model (4) are identified from the furnace step response by simple methods, and control law (5) is available as a standard function in any industrial controller.

N.B. Almutairi and M. Zribi designed two sliding mode controllers for a tempered glass furnace [16]. Their objective is to drive the temperatures of the glass plate and of the upper and lower furnace walls to a common setpoint. According to the simulation results, the controllers are robust to parameter changes and disturbances, and the controller based on state-dependent coefficient factorization performed better than a fuzzy PID controller. In sliding mode control, a sliding surface is formed from the error and its rate of change, and the control action drives the system state onto this surface. In general form:

$$s = \dot{e} + \lambda \cdot e, \quad u = u_{eq} - K_s \cdot \text{sign}(s), \quad (6)$$

where s is the sliding variable; $\lambda > 0$ is the surface parameter; u_{eq} is the equivalent control; K_s is the gain of the switching (relay) part. The robustness of such a controller depends on the accuracy of the process model.

In recent years, reinforcement learning methods have been actively applied. C. El Mazgualdi et al. developed a decision system based on a deep Q-network (DQN) and a neural network model for heating tempered automotive glass in an electric furnace [17]. The system selects the glass transfer speed and zone temperatures according to the desired outlet temperature of the glass, thereby automating the recipe that is usually chosen by trial and error. In a subsequent work, the approach was extended to minimize energy consumption while maintaining product quality [18]. H. Yu et al. proposed an improved double deep Q-network method for glass furnace temperature control [19]. A notable feature of this work is that controller robustness was evaluated by simulation under realistic disturbances, including fuel pressure fluctuations and production interruption events. In DQN-based methods, the agent learns the action-value function by approximating the target value based on the Bellman equation:

$$y_t = r_t + \gamma \cdot \max_{a'} Q(s_{t+1}, a'; \theta^-), \quad (7)$$

where s_t is the furnace state (temperatures, speed, etc.); a is the control action (zone temperature, transfer speed); r_t is the reward (depending on quality and energy consumption); γ is the discount factor; θ^- are the parameters of the target neural network. This method does not require an exact process model, but a simulator or a large amount of data is needed for training.

Research on glass furnace automation is also carried out in Uzbekistan. N.R. Yusupbekov and U.U. Kholmanov analyzed the development trends of glass furnaces and their monitoring and control systems [21]. U.U. Kholmanov proposed an advanced control system for the thermal parameters of a glass melting furnace and showed the feasibility of using fuzzy control [20]. The reviewed control methods are summarized in Table 1.

Table 1.

Temperature control methods for glass furnaces

Ref.	Object	Control method	Controlled variables	Validation
[15]	Glass melting furnace	FOPDT model + PI + fuzzy rules (cascade)	Furnace temperature	Industrial implementation

[16]	Tempering furnace	Sliding mode control (two types)	Glass, upper and lower wall temperatures	Simulation
[17]	Electric furnace for tempered automotive glass	DQN + neural network model	Glass transfer speed, zone temperatures	Offline decision system
[18]	Tempered glass heating process	DQN, PPO, A2C + random forest	Heating parameters, energy consumption	Production process case
[19]	Glass furnace	Improved DDQN	Fuel, air flow, inlet air temperature	Simulation with interruption events
[20]	Glass melting furnace	Parametric control scheme, fuzzy control	Flame temperature, excess oxygen, glass level, flue gas pressure	Simulation

The reviewed works show that intelligent control methods have been tested mainly in simulation, whereas industrial implementation has been reported mostly for relatively simple and interpretable schemes [15].

3. MATERIALS AND METHODS

The sources for the review were selected through keyword searches in international scientific databases. Works directly related to the bending of automotive glass or to the control of glass production furnaces were considered. The selected approaches were compared using five criteria relevant to automation: accuracy, computational speed, data requirements, feasibility of PLC implementation and level of validation. To illustrate the behavior of the process during an unplanned stoppage, simplified analytical estimates and a lumped thermal model were used, as described below. In gravity bending (sagging), a pair of glass sheets intended for a windshield is placed on a mold and carried on carriages successively through the zones of a continuous heating furnace. Typically, the furnace consists of preheating, heating, bending and cooling zones. When heated to the softening range, the glass takes the shape of the mold under its own weight and is then cooled at a controlled rate.

The viscosity of glass depends strongly on temperature: in the softening range, a relatively small change in temperature changes the viscosity several times [3]. Therefore, the degree of bending is determined not only by the temperature but also by the time the glass spends in the high-temperature zone; in other words, the bending result depends on the temperature-time regime. The temperature dependence of viscosity is often described by the Vogel-Fulcher-Tammann (VFT) equation [3]:

$$\lg \eta(T) = A + \frac{B}{T - T_0}, \quad (8)$$

where η is the dynamic viscosity, Pa·s; T is the temperature, K; A , B , T_0 are empirical coefficients depending on the glass composition.

The importance of the temperature-time regime can be shown with a simplified estimate. Using the analogy between elastic and viscous problems, the central deflection rate of a simply supported glass strip of length L and thickness h under its own weight can be estimated in the beam approximation as:

$$\dot{w} = \frac{5 \cdot \rho \cdot g \cdot L^4}{96 \cdot \eta(T) \cdot h^2}, \quad (9)$$

where ρ is the glass density, kg/m³; g is the gravitational acceleration, m/s². According to (9), the deflection rate is inversely proportional to viscosity. Therefore, if the glass remains stationary in the bending zone for an additional time Δt , the excess deflection is

$$\Delta w \approx \dot{w}(T) \Delta t, \quad (10)$$

which, according to (8), increases sharply with temperature. Expressions (9)-(10) are qualitative estimates only: in the real process, the mold shape, temperature non-uniformity and large deformations must be taken into account [5, 9].

Since glass is semitransparent, heat is transferred not only through the surface but also by radiation across the thickness, which complicates heat transfer calculations [2]. In the one-dimensional approximation across the thickness, the temperature field in a glass sheet is described by [2, 9]:

$$\rho c_p \frac{\partial T}{\partial t} = \frac{\partial}{\partial z} \cdot \left(k \frac{\partial T}{\partial z} \right) - \frac{\partial q_r}{\partial z}, \quad (11)$$

where c_p is the specific heat, J/(kg·K); k is the thermal conductivity, W/(m·K); z is the coordinate across the thickness, m; q_r is the radiative heat flux density inside the glass, W/m². The boundary condition at the glass surface accounts for convective and radiative heat exchange:

$$-k \frac{\partial T}{\partial z} \Big|_s = h_c \cdot (T_s - T_g) + \varepsilon \cdot \sigma \cdot (T_s^4 - T_w^4), \quad (12)$$

where h_c is the convective heat transfer coefficient, W/(m²·K); T_s , T_g , T_w are the temperatures of the glass surface, furnace gas and furnace walls, respectively; ε is the surface emissivity; σ is the Stefan-Boltzmann constant. The simplest way to account for internal radiation is the Rosseland approximation, in which radiation is represented as an additional thermal conductivity [8, 9]:

$$k_r = \frac{16 \cdot n^2 \cdot \sigma \cdot T^3}{3 \cdot \beta_R} \quad (13)$$

where n is the refractive index; β_R is the Rosseland mean extinction coefficient, 1/m.

If the glass is thin and the temperature difference across the thickness is small (Biot number $Bi = h_c h / (2k) \ll 1$), equations (11)-(12) reduce to a lumped-parameter model:

$$\rho \cdot c_p h \frac{dT}{dt} = 2[h_c \cdot (T_g - T) + \sigma \cdot v \cdot (T_w^4 - T^4)] \quad (14)$$

Model (14) assumes symmetric heating from both sides and allows fast calculation of the mean glass temperature over time, which makes such models convenient for control systems. In the calculations, the zone temperature was taken as 650 °C, the initial glass temperature as 600 °C, and material properties as typical approximate values for soda-lime glass ($\rho = 2500$ kg/m³, $c_p = 1200$ J/(kg·K), $\varepsilon = 0.9$, $h_c = 10$ W/(m²·K)). These parameters are nominal, and the results are given to illustrate the qualitative behavior of the process.

The main quality indicators of the bending process are the deviation of the bent shape from the specified shape (bending depth) [12], surface stresses at the glass edge [10] and optical distortion. Thus, the main task of bending process control is to ensure the required temperature-time regime for different product types in the presence of disturbances.

4. RESULTS AND DISCUSSION

4.1. Glass temperature during an unplanned stoppage

The change in temperature of the glass stopped in the bending zone, calculated by model (14), is shown in Figure 1.

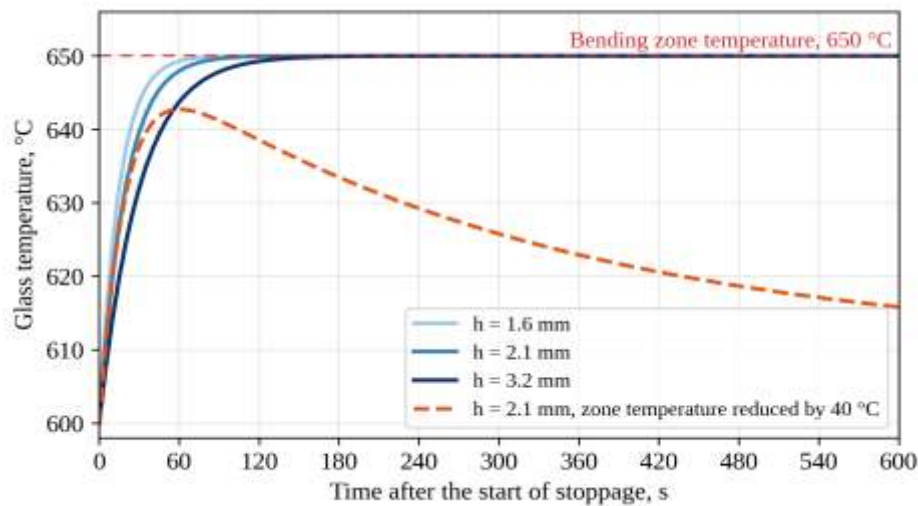


Figure 1. Glass temperature during a stoppage in the bending zone (calculation by model (14))

According to the calculation, if the zone temperature is unchanged, glass 1.6-3.2 mm thick reaches the zone temperature within 1-2 minutes. Hence, during a long stoppage the glass remains at the full zone temperature for almost the entire time, and excess deflection accumulates in proportion to time according to (10). When the zone temperature is reduced, the glass temperature decreases at a rate limited by the thermal inertia of the furnace walls. This shows that the control action should be applied as soon as the stoppage begins.

4.2. Comparative analysis of the approaches

To compare the approaches, five criteria were selected that determine whether a method can be transferred from research to an industrial control system. Accuracy characterizes how well a model reproduces the glass temperature and shape. Computational speed determines whether the method can be executed within the scan cycle of a PLC or SCADA system, that is, in real time. Data requirements reflect the effort needed to build and identify the model: physics-based models need temperature-dependent material properties and boundary conditions, whereas data-driven models need sufficiently long archives of process and quality data. The feasibility of PLC implementation is especially important for plants operating older-generation controllers with limited memory and computing power. Finally, the level of validation shows whether the results were confirmed only in simulation, by laboratory experiments or under industrial conditions.

Each group of approaches was evaluated on a three-level scale (A, B, C) on the basis of the information reported in the reviewed works. The grades are qualitative and reflect the typical properties of each group rather than the performance of individual implementations; nevertheless, they make it possible to compare the strengths and weaknesses of the approaches from the standpoint of an automation engineer.

A comparison of the reviewed approaches from the standpoint of their application in automation systems is given in Table 2.

Table 2.

Comparative characteristics of modeling and control approaches for the bending process

Criterion	Physics-based models [4-9]	Simplified and data-driven models [10-14]	Classical and hybrid control [15]	Intelligent control methods [16-19]

Accuracy	A	B (within the data range)	B (model-dependent)	A (in simulation)
Computational speed	C	A	A	B
Data requirements	C (material properties, boundary conditions)	B (production data)	A	C (detailed model or large data set)
PLC implementation	C (offline only)	A	A	C
Level of validation	B (experiments and measurements)	B (simulation and real data)	A (industrial implementation)	C (mainly simulation)

Note: A - good, B - medium, C - low. The grades show how convenient the method is for use in production: for example, A is given when little data is required or the calculation is fast, and C when much data is required or the calculation is slow.

Table 2 shows that the approaches complement each other. Physics-based models are convenient for understanding the process mechanism, designing furnaces and generating data for other models, whereas simplified and data-driven models are suitable for real-time process control. Surrogate models [14] may serve as a link between these two groups.

4.3. Critical stoppage time

Most of the reviewed works address the normal operating mode: maintaining a setpoint temperature, selecting a recipe or stabilizing product quality. Disturbances were considered in some works to assess controller robustness [16], while production interruptions were considered only for a glass melting furnace in simulation [19]. Among the reviewed sources, no work was found on assessing the state of the glass and controlling the process during an unplanned stoppage of a bending furnace. Meanwhile, a bending furnace simultaneously holds several glass sheets at different stages, and any change of the regime affects all of them [1].

The importance of this problem can also be shown with the expressions of Section 3. Model (14) estimates the change in glass temperature during a stoppage, and expressions (8)-(10) estimate the accumulation of excess deflection at this temperature. If the permissible deflection deviation is $[\Delta w]$, the critical time after which a defect occurs can be estimated from (10) as:

$$t_{cr} \approx \frac{[\Delta w]}{\dot{w}(T)} = \frac{96 \cdot \eta(T) \cdot h^2 \cdot [\Delta w]}{5 \cdot \rho \cdot g \cdot L^4} \quad (15)$$

According to (15), the critical time is proportional to the square of glass thickness and to viscosity; that is, the permissible stoppage time decreases sharply for thin glass at high temperature. The relative dependences following from (15) are shown in Figure 2.

According to Figure 2, when the glass thickness increases 1.6 times, the critical time increases 2.56 times, whereas the same increase in windshield length shortens it approximately 6.5 times. Therefore, when windshields of different sizes are produced in the same furnace, each product type must be considered separately in stoppage control. Exact critical time values should be determined from experiments or production data.

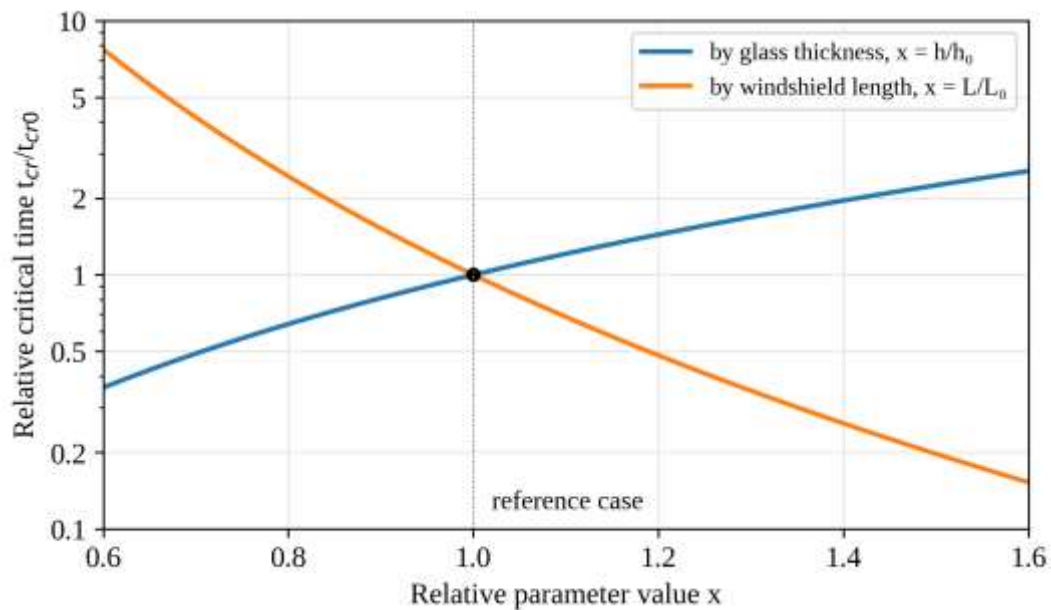


Figure 2. Relative critical time versus glass thickness and windshield length (calculation by expression (15))

4.4. Implementation aspects and open problems

Industrial enterprises often use older-generation PLCs. Under such conditions, it is difficult to implement complex intelligent algorithms, and solutions with interpretable results expressed as simple logical rules are preferable in practice. The regression models of Makarov et al. [10-12] and the hybrid system of Moon et al. [15] demonstrate the effectiveness of this approach. In addition, large amounts of process data are accumulated in SCADA systems and quality control logs, but they are rarely used in control decisions. The methodology of developing and deploying data-driven models in industry [13] shows a way to use this opportunity.

5. CONCLUSION

Methods of modeling and control of thermal regimes in the bending of automotive glass were classified into three groups: physics-based models, simplified and data-driven models, and furnace temperature control methods. Physics-based models provide the most detailed information on the process but, due to their computational complexity, are not used directly in real-time control. Simplified and data-driven models are more suitable for control systems, and their effectiveness in production has been demonstrated by regression models and industrially deployed prediction systems. Intelligent control methods (sliding mode control, reinforcement learning) have shown high performance in simulation, but their industrial implementation, especially at enterprises with older-generation controllers, remains limited. Most of the reviewed studies address the normal operating mode, while assessing the glass state and controlling the process under abnormal modes such as unplanned stoppages of a bending furnace remains insufficiently studied. Control of abnormal modes, control-oriented simplified thermal models, hybrid approaches combining production data and physics-based models, and interpretable control algorithms are promising directions for future research.

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