Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Model Predictive Control of Cavity Pressure in an Injection Moulding Process

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Abstract: Cavity pressure control is a means of improving repeatability and product quality in injection moulding processes. As the system behaviour is greatly dependent on the mould - which is interchangeable and typically designed and manufactured independently of the machine's control system - challenges arise in designing a controller that yields high performance and robustness to be suitable for universal use. A cavity pressure controller intended to be used for a wide variety of moulds will likely need some form of reparametrisation. In order to gain user acceptance, the process of manual or automatic parametrisation of the controller to a new mould needs to be simple enough to be performed and understood by staff that are not necessarily control experts. Addressing this issue, the authors suggest an approach using a Model Predictive Controller that is based on a physically motivated grey-box model. The model is simple enough to be intuitively checked for plausibility but sophisticated enough to reproduce the dominant behaviour of the system. For automated parametrisation, a strategy based on two experiments is suggested. The experiments are tailored to be suitable for incorporation into the regular production process. The concept is presented and first experimental results are shown.

Keywords:
Model-based control, Predictive control, Pressure control, Injection moulding, Physical Models, Closed-loop identification, Process parameter estimation, Production systems, Self-adjusting sytems, Self-optimizing systems.

1. INTRODUCTION

Injection moulding is one of the most important production technologies today. Although mainly used in mass production, the demands on quality for injection moulded parts constantly rise. One very important quality aspect is the final weight of the product, that is significantly influenced by packing/holding pressure, mould temperature and melt temperature. Several strategies are described in literature to control these process variables (e.g. Chen and Turng [2005], Rafizadeh [1996]). In Smud et al. [1991], Yang and Gao [1999] Gao et al. [2001] feasible solutions to control the packing/holding pressure are presented. Approaches to control the mould temperature are introduced in Saito and Satoh [2002], Gao et al. [1993].
Without an effective mould temperature control the cooling behaviour of the mould varies with temperature fluctuations within the machine and its surroundings. This varying cooling behaviour leads to significant deviations in part weight. In order to compensate these effects, the concept of 'pvT-Optimisation' has been introduced at the Institute of Plastics Processing (IKV) at RWTH Aachen University (see Matzke [1985], Michaeli and Gruber [2005], Hopmann et al. [2011]). Based on measurements of the temperature and the pressure in the mould, a reference trajectory for cavity pressure is generated by pvT-Optimisation. Using this trajectory as input for a cavity pressure controller, deviations in final product weight could be significantly reduced. Still, this concept could not yet be established in manufacturing machines. One challenge to overcome is the development of a robust control concept that is able to be adjusted to different moulds. This becomes especially tough as the moulds and sensors that are needed for implementation of the control concept are typically developed, manufactured and implemented independently of the machine. Therefore the developer of the controller does not know about the mould and sensor properties. Also, in order to be accepted by manufacturing companies, a control concept that will likely incorporate some kind of process identification will need to be able to be run systematically and simple enough to be accepted for everyday use. In order to achieve this, the authors suggest a Model Predictive Control (MPC) approach (see Bemporad [2006], Rawlings [2000]) that is based on a physically motivated, intuitive process model in combination with an identification procedure that is based on established ways of controlling the injection moulding process.

This paper is structured as follows. First, the injection moulding process is shortly introduced. Then, the reference generation through pvT-Optimisation is explained. The physically motivated model and the identification strategy used for the MPC is quickly reviewed. In the end, the Model Predictive Controller is described and experimental results are shown.

2. THE INJECTION MOULDING PROCESS

In injection moulding, heated liquified plastic material is driven into a mould by the means of a moveable screw. In the mould, the material cools down and solidifies, forming the final part. After solidification, the mould is opened in the parting plane, allowing for release of the solidified part (see also Rafizadeh [1996], Haman [2003]).
From a control perspective, two phases of the process are of special interest: the injection phase and the pressure holding phase. In the injection phase, the raw molten material is forced into the empty mould. The goal is to conduct this phase as fast as possible in order to save machine time and therefore increase productivity. Limitations exist with respect to the speed of the screw, as fast movement can also damage the polymer chains in the material, reducing product quality. The second phase, which will be considered in this paper, is called the pressure holding phase. It covers the time needed to cool the melt in the mould cavity and to finally solidify. During this cooling phase, the specific volume of the material decreases according to its thermodynamic pvT-behaviour, referred to as shrinking. As this could potentially lead to an incomplete filling of the mould, the pressure is kept at a high level during this phase so that an afterflow of molten material compensates for this shrinking (see Hopmann et al. [2011]). However, this afterflow can have negative effects on product quality, so it is desired to keep it as low as possible.

3. REFERENCE GENERATION THROUGH PVT-OPTIMISATION

There are many possible ways to guide the process through the pressure holding phase. Typical implementations include the control of screw pressure to a constant level or the setting of a low constant screw velocity in order to compensate the shrinking effects (see Schiffers [2009]). Both strategies only incorporate feedback control of values measured at machine level. That way, disturbances effecting the process path outside the machine are neglected by the machine controller. For example, the pressure in the mould is not taken into account by the control strategy, leaving room for process deviations. Especially temperature fluctuations, caused for example by convective heat flow due to air movement in a production facility, can have significant influence.
In order to address this issue, significant efforts have been made to measure the actual temperature and the pressure of the material in the mould and to incorporate these measurements into the control strategy. At the Institute of Plastics Processing, the strategy of 'pvT-optimisation' has been developed (see Michaeli and Gruber [2005], Hopmann et al. [2011]). The idea is to control cavity pressure in a way that the specific volume (and therefore the mass) of the melt in the cavity is kept constant whenever possible. In the ideal case, very high cavity pressure would be enforced at the beginning of the aftercooling phase and the pressure would gradually be lowered with dropping temperature so that the shrinking of the material would theoretically not cause any additional flow of material into the mould.
Figure 1 shows the actual reference trajectory for a typical melt material as displayed in the pvT-diagram. In practice, the aforementioned pressure course cannot be enforced throughout the whole process, as with typical process temperatures, the values of pressure that would be needed in the beginning and at the end of the aftercooling phase are unreasonably high. Therefore, they are limited to a maximum value (Course A-B-C instead of A-B'-C) and to ambient pressure (Course D-E-F) respectively.

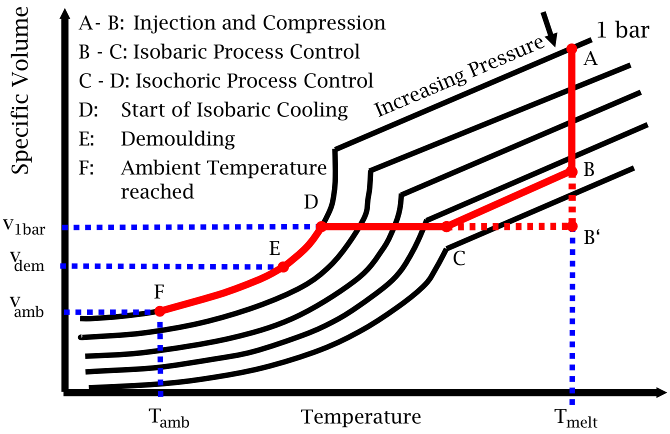

Fig. 1. Typical Reference Pressure Trajectory in pvT-Optimised Cycle for Semi-Crystalline Thermoplastics (see Hopmann et al. [2011]).

The pvT-diagram characterises the thermodynamic properties of the material by describing its specific volume as a function of pressure and temperature. This function is used to find the reference value for cavity pressure, depending on the current melt temperature, that results in the desired specific volume. Due to nontrivial online measurement of the melt temperature, it is for now determined by a so-called cooling equation (see [Matzke, 1985]). It is used to estimate the melt temperature as a function of time and the initial temperatures of the mould and the melt material

$$T_{CAV}(t) = T_{M,0} + (T_{melt} - T_{M,0}) \cdot \frac{8}{\pi^2} \cdot \exp\left(-a_{eff} \cdot \left(\frac{\pi}{s}\right)^2 \cdot t\right), \quad (1)$$

where $T_{M,0}$ denotes the initial mould temperature, T_{melt} the initial melt temperature, s the wall thickness of the formed part and a_{eff} the effective heat conduction coefficient. In operation, actual temperature measurements of the mould is taken at the beginning of each cycle to parametrise the cooling equation and to adjust to temperature fluctuations in the mould.

4. PHYSICAL-BASED SYSTEM MODEL AND PARAMETER IDENTIFICATION PROCEDURE

In order to better understand the process and to gain a process description that can be used in a Model Predictive Controller, a simple physically motivated model of the injection moulding process as described in Hopmann et al. [2013] was used. The principle sketch of the model is depicted in figure 2. The intention was to find a description that on the one hand is able to sufficiently describe the process behaviour and on the other hand is still intuitive so that it can later be parametrised by staff that are not necessarily control experts.

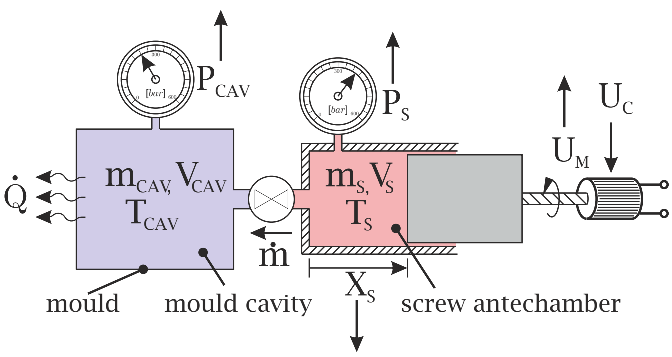

Fig. 2. Principle Sketch of Physically Motivated Control Model

The injection moulding process is described by two pressure vessels that are interconnected. The first pressure vessel represents the screw antechamber. A closed-loop temperature control is implemented to keep the melt in the screw antechamber at $T_S = 240\,°C$. It is assumed to be constant, therefore no heat loss is considered in the first vessel. The volume of the screw antechamber is determined by the screw position X_S, which results from the screw velocity $\dot{X}_S$. The demand value for the screw velocity U_C is the output of the controller. U_M denotes the actual measured value of the screw velocity. The second vessel represents the mould cavity. In contrast to the first vessel, a heat flow $\dot{Q}$ out of the melt is taken into account. This heat flow $\dot{Q}$ is the cause for the shrinkage of the melt. Its effect is described by the cooling calculation equation (1). Furthermore, the cavity volume V_{CAV} is assumed to be constant. The pressures in both vessels, P_S and P_{CAV}, are calculated as a function of the temperatures and specific volumes of the material they contain. This function is a material property and is typically available in the form of a pvT-table (see figure 1). The mass flow $\dot{m}$ between the two vessels is attributed on the pressure difference between them. A basic valve equation

$$\dot{m}(P_S, P_{CAV}, t) = K(t) \cdot \sqrt{P_S - P_{CAV}} \tag{2}$$

is used as basis for extrapolation, where geometric dependencies and the material viscosity are represented by the time-dependent mass flow coefficient K. Measurements are taken of the pressures P_S and P_{CAV} within the screw antechamber and the mould cavity as well as the velocity $\dot{X}_S$ and the position X_S of the screw. For the control model, it is assumed that the actual screw velocity follows its reference value without error: $\dot{X}_S \approx U_C$.

4.1 Model Equations

To summarise, the model results in the equations

$$\begin{aligned}
\frac{\mathrm{d}X_S}{\mathrm{d}t} &= U_C \\
\frac{\mathrm{d}m_S}{\mathrm{d}t} &= -\dot{m}(P_S, P_{CAV}, t) \\
\frac{\mathrm{d}m_{CAV}}{\mathrm{d}t} &= \dot{m}(P_S, P_{CAV}, t) + \dot{m}_{corr}
\end{aligned} \tag{3}$$

with

$$\begin{aligned}
\dot{m} &= K(t) \cdot \sqrt{P_S - P_{CAV}} \\
P_S &= \mathrm{pvT}(v_S, T_S) \\
v_S &= \frac{V_S}{m_S} \\
V_S &= A_S \cdot X_{S,0} + V_{S,rem} \\
P_{CAV} &= \mathrm{pvT}(v_{CAV}, T_{CAV}) \\
v_{CAV} &= \frac{V_{CAV}}{m_{CAV}} \\
V_{CAV} &= const,
\end{aligned} \tag{4}$$

where the position X_S and the masses m_S and m_{CAV} of the melt in the screw antechamber and in the cavity mould are the states of the system. V_{CAV} denotes the effective volume of the cavity mould and $V_{S,rem}$ denotes the effective remaining volume of the screw antechamber at $X_S = 0$. A_S denotes the cross-sectional area of the screw. In order to model the shrinking of the material, a fourth state, $\dot{m}_{corr}$ is introduced. It represents a virtual loss of mass in the cavity and leads to a pressure drop in the cavity that is equivalent to the pressure drop/shrinking caused by the heat loss $\dot{Q}$. This state will serve as a disturbance state and will be observed by an Extended Kalman Filter which is described in section 5. It should be stated at this point that the authors first attempted to base the equations up on the cavity temperature T_{CAV} as a fourth state, which would support the desire to obtain a very interpretable model. However, as the pressure of the material is highly dependent on temperature, and the simplifications made by modeling the melt in the cavity as a homogeneous mass with a uniform temperature are quite strong, a ‘temperature state’ would also merely be a representative value. Therefore, a virtual mass loss, which is easier to implement, was introduced.

4.2 Parametrisation of Valve Equation

In order to parametrise the time-dependent coefficient $K(t)$ in equation (2), a test run is conducted. For details see Hopmann et al. [2013]. In short, the process is run at constant screw pressure P_S. For this, a relatively simple and robust PI-controller is used. Process data are shown in figure 3. Based on the aforementioned assumption of the temperature T_S of the melt in the screw antechamber being constant, its specific volume v_S needs to be constant as well. This allows to estimate the mass flow $\dot{m}$ by calculating the derivative of the volume V_S. In this case, $\dot{V}_S$ can be calculated using the measurement of the screw position X_S:

$$\begin{aligned}
P_S, T_S = \mathrm{const} &\Rightarrow v_S(P_S, T_s) = v_{S,0} = \mathrm{const} \\
&\Rightarrow \dot{m}(t) = \frac{1}{v_{S,0}} \dot{V}_S = \frac{1}{v_{S,0}} \cdot A_S \cdot \dot{X}_S.
\end{aligned} \tag{5}$$

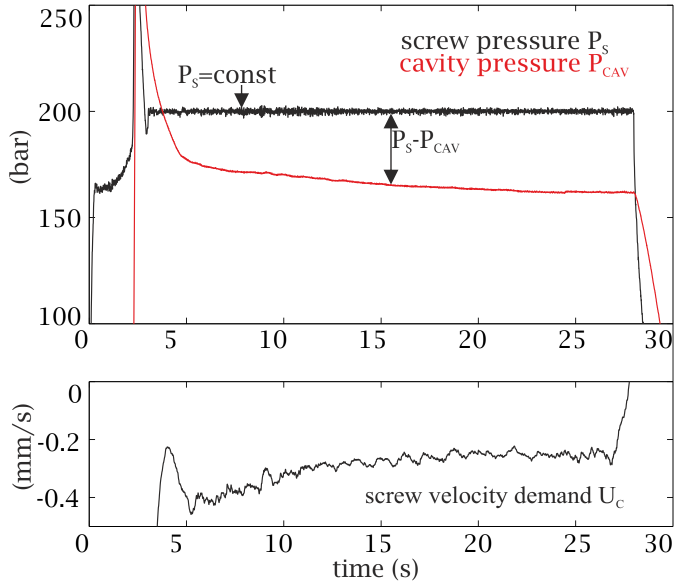

Fig. 3. Identification Cycle: A simple and robust PI-controller for screw pressure is implemented to create process data suitable for parametrisation of the valve equation (2).

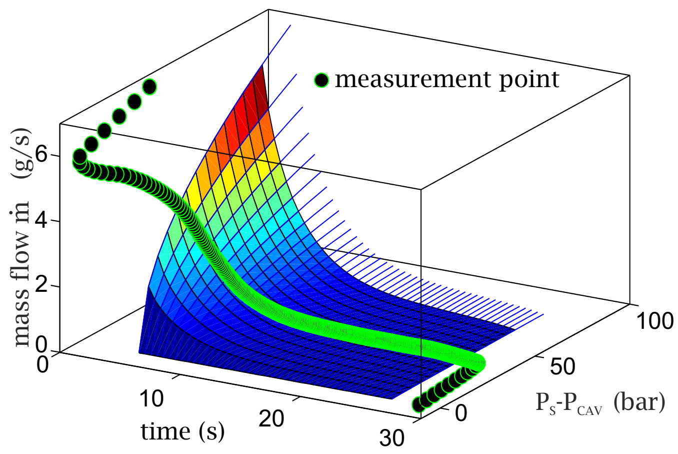

Fig. 4. Parametrisation of Valve Equation: For each point in time, nearby measurement values taken from the test cycle are used to determine $K(t)$.

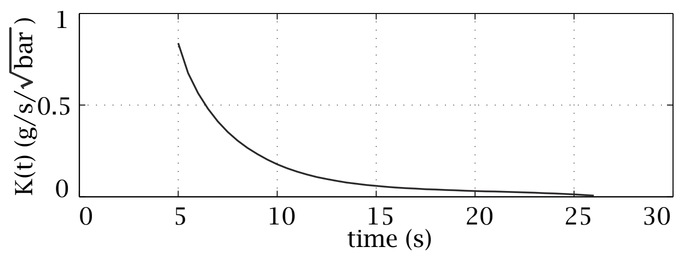

Fig. 5. Parametrisation of Valve Equation: Result

Using the estimates of $\dot{m}(t)$ and the corresponding measurements of P_S and P_{CAV}, the time-dependent parameter $K(t)$ of the valve equation (2) is determined and stored in a look-up table. The results are displayed in figures 4 and 5. The effect of the rising viscosity due to the cooling of the melt temperature can clearly be seen. At later times, a given pressure difference results in significantly lower mass flow. Note that the approach at this point in time is only valid within the pressure holding phase. In the injection phase, the proposed modeling assumptions are not valid.

There are two main motivations for the proposed procedure. Firstly, the procedure allows to make use of process-specific characteristics in order to gain a reasonable estimate of the mass flow that is otherwise hard, if not impossible to measure. Secondly, it is based on a test run that has the potential to be easily implemented into a typical production workflow. Controllers designed to run the injection moulding process at constant screw pressure are well established and often already implemented into production machines. Therefore, it is unlikely that the test run would cause the process to reach an unstable state that would interrupt the production workflow.

4.3 Parametrisation of Effective Volumes

Apart from the time-dependent viscosity, the dynamic behaviour of the system described by the equations in section 4.1 is significantly influenced by the values chosen for the effective volumes of the screw and the cavity. In order to gain useful parametrisation data, the response of the cavity pressure signal to impulse-like inputs of the actuator variable was recorded. This can only be conducted with the process already running near the desired operating point. If the process is run outside typical values, for example if the pressure levels are two low, the part produced might not eject properly. If this happens, a manual ejection of the part, which can be very time-consuming, will typically be necessary. Therefore, the experiment was performed in two steps. First, a simple, robust, but low-performance PI-controller was implemented, performing a cycle at constant cavity pressure. The control inputs $U_{C,ID}(t)$ demanded by the PI controller during this cycle were recorded and then superimposed with impulse inputs $I(t)$:

$$U^*_{C,ID}(t) = U_{C,ID}(t) + I(t). \tag{6}$$

Then the process was run again in an open-loop mode, using $U^*_{C,ID}(t)$ as control input. The results are shown in figure 6.

The plausibility of the model can be explained using these trajectories. Applying an impulse to the actuator variable, which corresponds to the screw velocity, effectively leads to a sudden reduction of available screw volume and therefore to an increase in screw pressure. The resulting pressure difference leads to a mass flow $\dot{m}$ into the cavity volume, leveling out the two pressures. Note that a significant offset exists between the two pressure signals. This difference corresponds to the pressure drop induced by mass flowing into the cavity due to shrinking. One can easily imagine that the volume of the screw cavity greatly influences the height of the first peak whereas the total volume of the screw and the cavity determines the ‘steady state’ increase in pressure. Using a simulation model, the values for V_{CAV} and V_S were manually chosen to best fit to the experimental data.

5. MODEL PREDICTIVE CONTROLLER

In the Model Predictive Controller, an affine model is used to predict the controlled outputs of the plant over

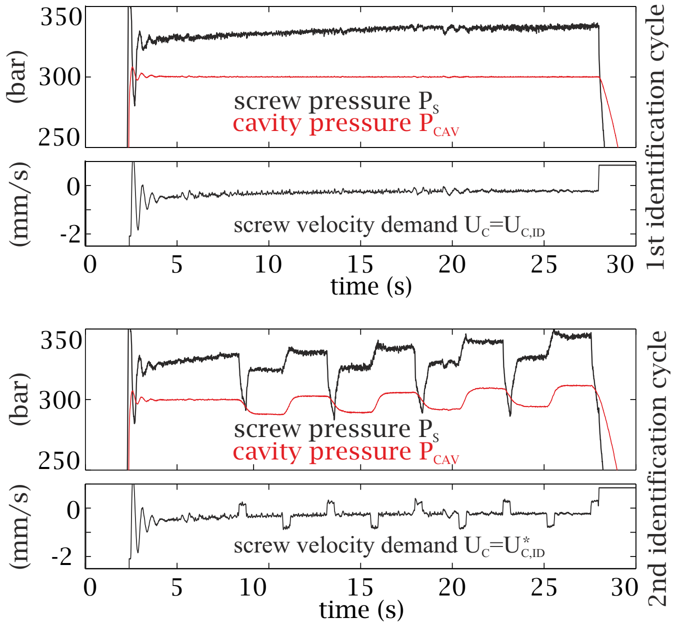

Fig. 6. Parametrisation of Effective Volumes: Two cycles are conducted in order to gain suitable parametrisation data.

a finite time horizon. This prediction is used to solve a finite horizon open-loop optimisation problem. An optimal control sequence

$$\Delta\mathbf{U}^* = \Delta\mathbf{U}^*_{(k|k)}....\Delta\mathbf{U}^*_{(k+H_p-1|k)} \tag{7}$$

for the prediction horizon H_P is calculated by the MPC algorithm. At the time instant k with $k \in 0,1,2,...,$ $(\cdot)_{(k+j|k)}$ denotes the prediction of the variable $(\cdot)$ for the time instant $k+j$ at time step k. After optimisation, the first control signal $\mathbf{U}(k) = \mathbf{U}(k-1) + \Delta\mathbf{U}(k \mid k)$ is applied to the system. The optimisation problem is solved at each sampling step. At the next time step a new optimisation is solved over a shifted prediction horizon. This procedure realises a feedback mechanism, which makes reference tracking and disturbance rejection possible. The formulation used here was chosen very close to an MPC implementation described in Albin et al. [2011]. Trough linearisation of the nonlinear model, the affine model used for prediction is updated at each timestep. That way, the nonlinearities in the system behaviour are accounted for up to a certain point. These nonlinearities mainly arise from the strongly time-dependent viscosity of the plastic material, its pvT-behaviour and the geometric dependencies described in equation (3). The model is calculated in the form

$$\begin{aligned} \mathbf{X}(k+1) &= \mathbf{A}^k \cdot \mathbf{X}(k) + \mathbf{B}^k \cdot \mathbf{U}(k) + \mathbf{f}^k \\ \mathbf{Y}(k) &= \mathbf{C}^k \cdot \mathbf{X}(k) + \mathbf{g}^k. \end{aligned} \tag{8}$$

Hereby, $\mathbf{X} \in \mathbb{R}^n$ denotes the state vector. $\mathbf{A}^k$, $\mathbf{B}^k$, $\mathbf{C}^k$, $\mathbf{f}^k$, $\mathbf{g}^k$ are constant matrices describing the affine models at time instant k.
As a physical-based model is used, the states, the inputs, and the outputs of the system are interpretable, they are selected as

$$\begin{aligned} \mathbf{X} &= [X_S, m_S, m_{CAV}, \dot{m}_{corr}]^T \\ \mathbf{U} &= [U_C] \\ \mathbf{Y} &= [P_{CAV}]. \end{aligned} \tag{9}$$

The optimisation is conducted with respect to the quadratic cost function

$$\begin{aligned} J = &\sum_{j=0}^{H_u-1} (\Delta\mathbf{U}^T_{(k+j|k)} \cdot \mathbf{R} \cdot \Delta\mathbf{U}_{(k+j|k)}) \\ &+ \sum_{j=1}^{H_p} [(\mathbf{Y}_{(k+j|k)} - \mathbf{Y}_{ref})^T \mathbf{Q} (\mathbf{Y}_{(k+j|k)} - \mathbf{Y}_{ref})] \end{aligned} \tag{10}$$

subject to

$$\begin{aligned} \mathbf{X}_{(k+j+1|k)} &= \mathbf{A}^k \cdot \mathbf{X}_{(k+j|k)} + \mathbf{B}^k \cdot \mathbf{U}_{(k+j|k)} + \mathbf{f}^k, \\ & \qquad\qquad j = 0, ..., H_p - 1 \\ \mathbf{Y}_{(k+j|k)} &= \mathbf{C} \cdot \mathbf{X}_{(k+j|k)} + \mathbf{g}^k, \quad j = 1, ..., H_p \\ \mathbf{U}_{Min} \leq \mathbf{U}_{(k+j|k)} &\leq \mathbf{U}_{Max}, \quad j = 0, ..., H_u - 1. \end{aligned} \tag{11}$$

H_u denotes the length of the control horizon. The weighting matrices $\mathbf{R}$ and $\mathbf{Q}$ are used to penalise changes $\Delta\mathbf{U}$ in the actuator signal as well as deviations from the reference trajectory $\mathbf{Y}_{ref}$. They are defined as:

$$\mathbf{Q} = \mathbf{I}, \quad \mathbf{R} = \lambda \cdot \mathbf{I}. \tag{12}$$

Here, λ serves as a tuning parameter. $\mathbf{U}_{Min}$ and $\mathbf{U}_{Max}$ are constraints on the absolute value of the controller output U_C. They are implemented in order to avoid excessive screw movement and to prevent damage. $\mathbf{I}$ is identity matrix. As not all states of the model used in the controller can be measured directly, an Extended Kalman Filter (EKF) based on the linearisation at the current operating point is used. As mentioned in section 4.1, the state vector is extended by a disturbance state $\dot{m}_{corr}$. The EKF is initialised after the injection, since the underlying model is not valid during the injection phase. In this phase, the screw is driven at a constant velocity $\dot{X}_S = \dot{X}_{S,inj}$ until the screw pressure reaches a turn-over pressure: $P_S > P_{S,inj}$. For the works described in this paper, P_S and $\dot{X}_{S,inj}$ were chosen manually.

6. RESULTS

The concept described above was implemented into an 'Arburg Allrounder 520 A' injection moulding machine using a PC-based, real-time capable controller solution. The sampling rate of the EKF and the Model Predictive Controller was set to $8\,ms$. The prediction was carried out over a horizon of $H_p = 25$ time steps. As control horizon, $H_u = 1$ was chosen. The control output is limited to $\mathbf{U}_{Max,Min} = \pm 2.1\,mm/s$. The controller is compared to the PI-controller used within the identification procedure. The results for an artificial reference profile are shown in figure 7.
Both controllers show stable behaviour and, if the dynamics in the reference trajectory are not to high, reasonable performance. However, it is notable that the MPC causes much lower overshoot than the PI-controller. The reason is that the optimisation in the MPC is aware of the limitations on the actuator variable. Therefore, no explicit

anti-windup strategy is necessary. Also, as the MPC uses a prediction of the reference value, it 'looks ahead' and anticipates upcoming changes in the reference value, as can be seen at the times 18 s and 23 s. Although it is likely that with proper tuning, the PI-controller could achieve a performance similar to the MPC in this reference case, it should be pointed out that the MPC was parametrised using a relatively intuitive procedure and with very low amount of additional tuning. Therefore, the main advantage is not necessarily to be seen in the direct performance comparison, but much more in the potential of the underlying methodology to be transferable to different moulds.

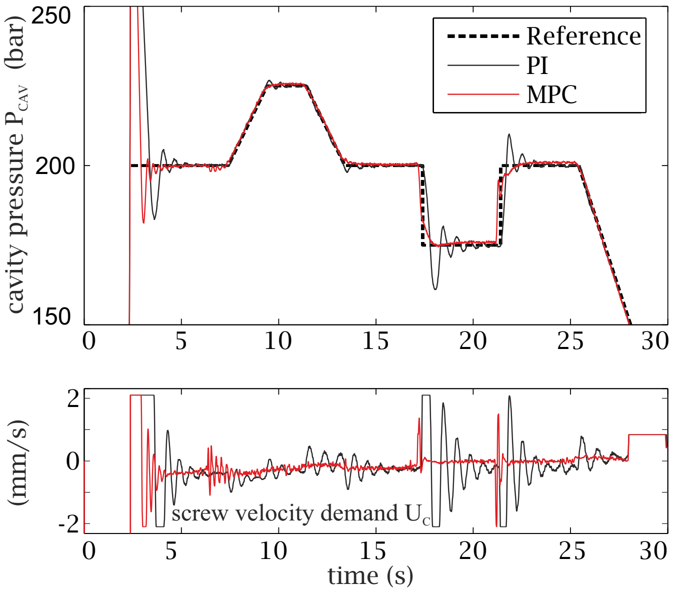

Fig. 7. Results: Model Predictive Controller is compared to PI-controller used in parametrisation procedure.

7. SUMMARY AND OUTLOOK

In this paper, a Model Predictive Controller for cavity pressure control in an injection moulding process was presented along with an underlying, physically motivated control model. The model is simple enough to be intuitively checked for plausibility. Also, the proposed experiments that were used to parametrise the model can be easily incorporated into a real-life workflow, as they are mostly based on well-established control strategies. Although a robust PI-controller for cavity pressure is used to conduct one of the experiments, this PI-controller does not necessarily need to yield high performance. Further research and experiments are planned to cross-verify how well the proposed concept can be transferred to other combinations of moulds and sensors.

ACKNOWLEDGEMENTS

The depicted research has been funded by the German Research Foundation DFG as part of the Cluster of Excellence "Integrative Production Technology for High-Wage Countries". We give thanks to ARBURG GmbH + Co. KG (Loburg, Germany) and SABIC Deutschland GmbH & Co. KG (Düsseldorf, Germany) for supplying the injection moulding machine and plastic material used in the experiments.

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