Iterative learning control for an injection unit of a plastic injection moulding machine

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Abstract

This paper deals with the application of an iterative control structure for the injection cycle of a displacement-controlled industrial injection moulding machine. Conventionally used controllers for mould filling and packing are feedback structures switching between controlling ram velocity and hydraulic pressure. The algorithm presented in this paper uses an iterative feedforward approach for both injection and packing phase together, thus overcoming the difficulties of pressure peaks resulting from the switching action of the controllers. This inversion-based iterative approach uses a nonlinear mathematical model of the injection unit which is used for an error minimization on the basis of a quadratic next-iteration cost criterion.

The application of the algorithm to a machine with a clamping force of 1600kN and injection unit size 650[1] leads to a significant error reduction with an exponentially decreasing error level. In addition, the algorithm demonstrates a way to recall the maximum dynamic potential of the displacement-controlled hydraulic drive system without reaching the stability limit.

KEYWORDS: iterative learning control, ILC, hydraulic drive, injection moulding machine, quadratic learning, nonlinear systems, displacement control.

1. Introduction

Many industrial applications, such as injection moulding or robotics, feature periodically repeating sequences. The performance of these systems that execute the same task multiple times can be improved by learning from previous cycles. Since conventional

[1] EUROMAP

(non-learning) controllers in non- or only slightly time-variant cycles yield the same error on each trial, the application of an iterative learning control (ILC) is feasible. The ILC algorithm behaves analogous to the human learning process. For example, it takes a long time to learn the high jump - a complex finite motion sequence. Comparable to the ILC, the errors of each trial have to be analysed to correct the motion sequence for the next trial.

The production of plastic parts via the primary shaping procedure of injection moulding requires a highly repetitive process in which the quality of the moulded parts greatly depends on the accuracy of the process. As the process is related to the nonlinear and time-variant characteristic of the drive system, a control structure which can easily be parameterized and works stably in a wide range of operating points is needed. ILC algorithms satisfy these requirements.

ILC algorithms can be classified according to the use of model information /1/. *Gain-type* ILC algorithms update the feedforward signal with the product of gain times the error sequence, the derivative or the integral of the error sequence. Thereby the gain has to be adjusted properly to guarantee process convergence. Yet, for many applications either convergence can be very slow or an exponentially increasing feedforward signal can occur. By using *model-type* ILC methods one is able to avoid the mentioned disadvantages via employing a model of the dynamics of the controlled system. This leads to the so-called “inverse problem”: For the computation of the feedforward signal update, the inverse dynamics of the plant has to be derived.

Iterative learning control was introduced by Arimoto /2/ in 1984, who developed the principle of iterative learning in robotics. His gain-type algorithm had a relatively simple structure, consisting of the previous error and an input term, often referred to as “betterment control”. In 1999 Havlicsek /3/ applied a similar algorithm to the valve-controlled filling and packing phase of an injection moulding machine for the first time. The algorithm, using a proportional-derivative update on the error, features different ILC designs for the filling and packing phase. It performs well, but the fill-to-pack transition leads to an oscillating error of the pressure. Subsequently, several papers about this issue were published, for example by Zheng /4/, who studied the transition between the injection and the packing phase for the gain-type algorithm. As a result, the control signal and the pressure transient became significantly smoother than at /3/.

The model-type ILC was developed by Amann /5/. His algorithm was the basis of Gao’s work /6/, using the cost function for a sampled-time linear system. He applied the algorithm to the ram velocity of an injection moulding machine, which shows a good level of convergence and robustness.

The difference between the mentioned publications and the present one is the application of a model-type norm-optimal ILC of a nonlinear system for the injection and the packing phase together. Based on the system model, a new ILC algorithm is suggested. The presented algorithm shows a great improvement compared to a simple feedback controller: with its help, disturbances over the cycles can be minimized. The approach facilitates a better use of the dynamic potential of the hydraulic drive system without leading to instability.

This paper is outlined as follows. In chapter 2 the relevant system of the injection unit is described. Chapter 3 covers the iterative learning algorithm and the minimization of the quadratic next-iteration cost criterion. Chapter 4 deals with the modelling of the displacement-controlled injection unit. While chapter 5 focuses on the simulation results, the performance test of the actual machine is discussed in chapter 6. Finally, the conclusions are drawn and an outlook for further investigations is given.

2. Process Description

Injection moulding machines are one of the most important series machines in stationery hydraulics. There is a huge variety of drive systems for the actuation of the injection unit. Against the background of rising energy costs, increasing attention is paid to displacement-controlled electrohydraulic drive systems. For this reason an ILC is applied to an injection unit shown in **Figure 1**.

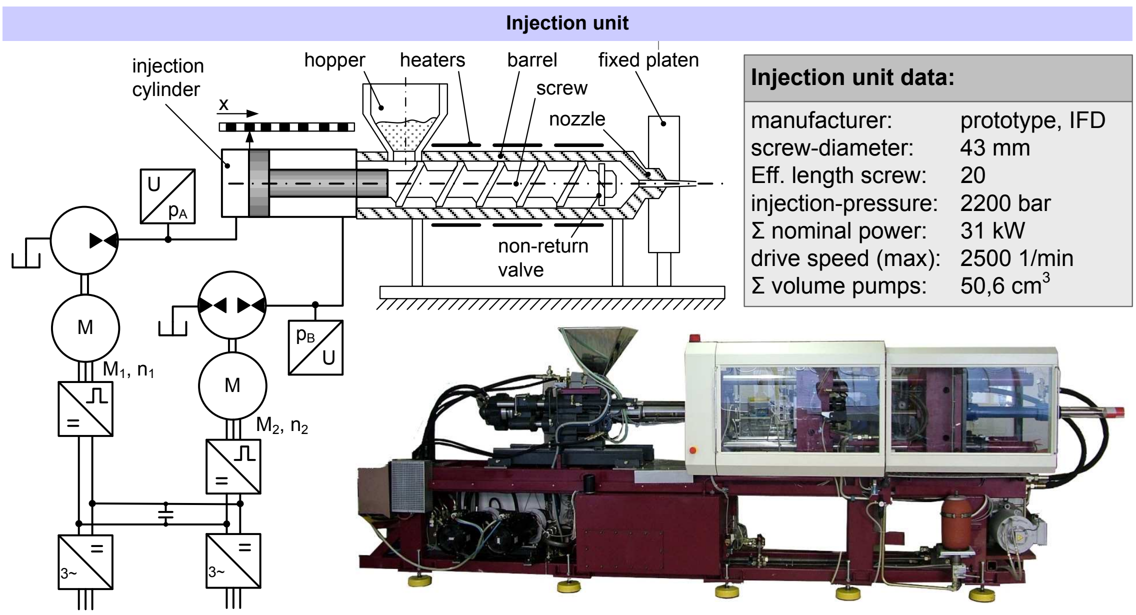

Figure 1: Injection moulding machine

The drive system consists of two displacement-controlled pumps acting on a differential cylinder. (Further possible connections via switching valves are left out for simplification). The injection process starts with the injection of plasticized material into the mould according to a (process-dependent) user-given trajectory for the ram position x moving the injection screw forward (injection phase). Once the mould is filled, the pressure within the mould rises and the speed-control is switched to the control of the injection pressure (packing phase). As often a sensor for mould-pressure is not available, the hydraulic pressure p_A (hereafter referred to as p) is controlled instead. The pressure trajectory has to be defined by the user according to material and mould characteristics. The product quality of plastic parts is considerably affected by the precision of the injection and packing phase and a minimal overshoot in the switching point sp.

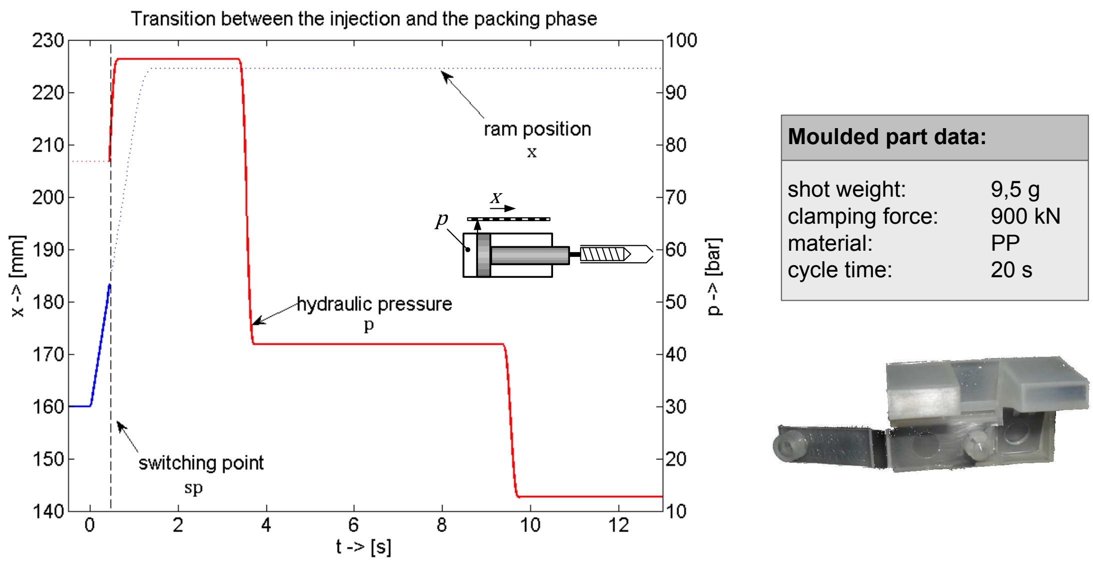

Figure 2: Desired trajectories and the transition between the injection and packing phase (left) and the used mould (right)

On the left side of **Figure 2** a typical injection process for the moulded part on the right side of Figure 2 is shown: Before the switching point is achieved, the controlled variable is the position x, afterwards the hydraulic pressure p. Good quality parts can be achieved with a smooth switching between these two phases at switching point sp. Hence, a control strategy which minimizes errors quickly and reliably is needed. The following section presents an ILC approach which satisfies these requirements.

3. Iterative Learning Control

The presented learning control is a model-based algorithm according to /5/. It uses the error between the desired trajectory $\underline{w}^{(N\times1)}$ and the measured signal $\underline{y_j}^{(N\times1)}$ of the last cycle to compute a feedforward signal $\underline{u}_{j+1}{}^{(N\times1)}$ for the next cycle according to equation (1). This is done offline after each cycle j.

$$\underline{u}_{j+1} = \underline{u}_j + \eta \cdot \underline{g}_j(\underline{w}, \underline{y}_j, \underline{u}_j) \quad (1)$$

The index j denotes the number of completed trials and therefore $j+1$ means the following trial. Since the ILC is a closed-loop control over the cycles but not during the cycle, a feedback controller G_r is needed to react to errors during the cycle according to **Figure 3**. For this, the feedback signal $u_r(k)$ has to be added to the feedforward signal $u_j(k)$ in each discrete time step k.

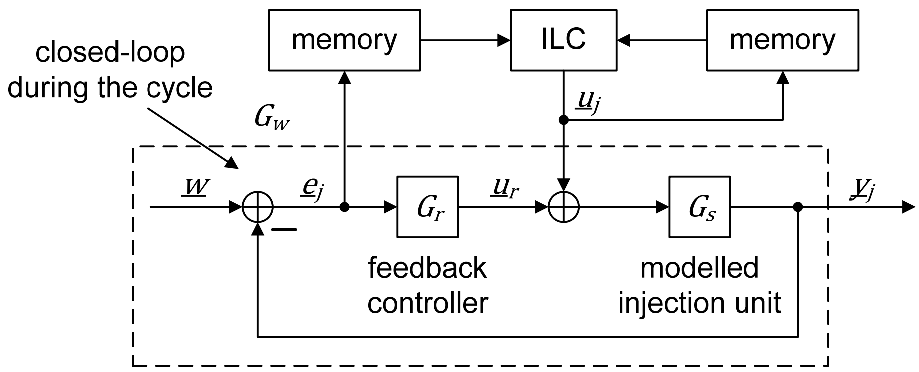

Figure 3: Block diagram of the ILC algorithm

The learning function $\underline{g}_j$ computes the input vector $\underline{u}_{j+1}$ offline with two objectives: minimizing the error $\underline{w} - \underline{y}_j$ of the last step and minimizing the change of the control signal $\underline{\Delta u}_j$.

3.1. Lifted System Representation

For the prediction of the system output $\underline{y}_{j+1}$ in the next cycle a lifted system representation is used. Nonlinear plants make it necessary to linearize the system along the desired trajectory $\underline{w}$ as described by Wagner in /7/. The result of this linearization is a matrix with the time variant impulse response $f_s(k,l)$ with $0 \leq k \leq N$ and $k \leq l \leq N$. The index k names the discrete time step of each impulse response and the index l represents the starting time step of the impulse responses. These time variant impulse responses establish the lifted system matrix $\underline{M}_s$. The prediction of the system output $\underline{y}_j$ for a given input signal $\underline{u}_j$ is obtained with equation (2), where $\underline{y}_r$ represents the inaccuracy of the used model as a disturbance at the output. This disturbance is omitted in the following, because it is invariant over the cycles.

$$\underbrace{\begin{bmatrix} y_j(0) \\ y_j(1) \\ y_j(2) \\ \vdots \\ y_j(N) \end{bmatrix}}_{\underline{y_j}} = \underbrace{\begin{bmatrix} f_s(0,0) & 0 & 0 & \dots & 0 \\ f_s(1,0) & f_s(1,1) & 0 & \ddots & 0 \\ f_s(2,0) & f_s(2,1) & f_s(2,2) & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & 0 \\ f_s(N,0) & f_s(N,1) & f_s(N,2) & \dots & f_s(N,N) \end{bmatrix}}_{\underline{M_s}} \cdot \underbrace{\begin{bmatrix} u_j(0) \\ u_j(1) \\ u_j(2) \\ \vdots \\ u_j(N) \end{bmatrix}}_{\underline{u_j}} + \underbrace{\begin{bmatrix} y_r(0) \\ y_r(1) \\ y_r(2) \\ \vdots \\ y_r(N) \end{bmatrix}}_{\underline{y_r}} \tag{2}$$

3.2. Cost Criterion

The norm-optimal iterative algorithm minimizes a quadratic next-iteration cost criterion, considering the control error and the change-rate of the feedforward signal. The cost criterion is specified over a complete cycle, including the switching point sp between the injection and packing phase. Therefore it is necessary to replace the general system output $\underline{y_j}$ with the ram position $\underline{x_j}$ and the hydraulic pressure $\underline{p_j}$ according to the desired control variable input. Since the cost criterion is specified to decrease the error in the next cycle, the used factors have to be apply for the next cycle $j+1$. Equation (3) describes the control errors between the given values w and the values in the next cycle $\underline{x}_{j+1}$, respectively $\underline{p}_{j+1}$.

$$\underline{e}_{x,j+1} = \underline{w}_x - \underline{x}_{j+1} \qquad \text{and} \qquad \underline{e}_{p,j+1} = \underline{w}_p - \underline{p}_{j+1} \tag{3}$$

The change of the feedforward signal between the actual and the following time step $\underline{\Delta u}_{j+1}$ is described by equation (4) and (5).

$$\Delta u_{j+1}(k) = \begin{cases} u_{j+1}(0), & k = 0; \\ u_{j+1}(k) - u_{j+1}(k-1), & 1 < k < N. \end{cases} \tag{4}$$

in matrix notation

$$\underline{\Delta u}_{j+1} = \underbrace{\begin{bmatrix} 1 & 0 & \cdots & 0 \\ -1 & 1 & \ddots & \vdots \\ 0 & -1 & \ddots & \vdots \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 1 \end{bmatrix}}_{\underline{M_\Delta}} \cdot \underline{u}_{j+1} \tag{5}$$

This means that a sharp increase of the feedforward signal within the cycle will be punished in the cost criterion. This contribution is necessary to prevent an exponential increase of the feedforward signal for reasons of stability. The quadratic next-iteration cost criterion J_{j+1} can now be derived (equation (6) and (7)).

$$J_{j+1} = \left\|\underline{e}_{x,j+1}\right\|^2 + \left\|\underline{e}_{p,j+1}\right\|^2 + \left\|\underline{\Delta u}_{j+1}\right\|^2 \tag{6}$$

in matrix notation results

$$J_{j+1} = \underline{e}_{x,j+1}^T \cdot \underline{Q}_x \cdot \underline{e}_{x,j+1} + \underline{e}_{p,j+1}^T \cdot \underline{Q}_p \cdot \underline{e}_{p,j+1} + \underline{\Delta u}_{j+1}^T \cdot \underline{Q}_u \cdot \underline{\Delta u}_{j+1} \tag{7}$$

where

$$\begin{aligned} \underline{Q}_x &= q_x \cdot \underline{I}^{(N\times N)} \cdot \underline{r}^{(N\times 1)} \qquad \text{with} \qquad r(n) = \begin{cases} 1, & n < sp \\ 0, & n \geq sp \end{cases} \\ \underline{Q}_p &= q_p \cdot \underline{I}^{(N\times N)} \cdot \underline{s}^{(N\times 1)} \qquad \text{with} \qquad s(n) = \begin{cases} 0, & n < sp \\ 1, & n \geq sp \end{cases} \end{aligned} \tag{8}$$

In equation (8) q_x and q_p are the weighting factors. Additionally, a smooth transition between the two phases is required from the weighting matrices. This is achieved through filtering of the weighting matrices. The weighting matrix $\underline{Q}_u$ is built up of a $N \times N$-dimensional diagonal identity matrix multiplied by the weighting factor for the change of the feedforward signal q_u. With the help of the three weighting factors it is possible to adjust the weighting ratio of the individual components in the cost criterion.

3.3. Minimization Of The Cost Criterion

For the minimization it is initially be necessary to replace the variables for the next cycle $j+1$ with variables of the actual cycle j in the cost criterion J_{j+1}. This is done with the prediction of the output via the lifted system matrix (2). The time-variant impulse responses are generated for the closed-loop system G_w in Figure 3, which means that the closed-loop with the feedback controller and the plant were used. To this end, the lifted system matrices $\underline{M}_{s,x}$ and $\underline{M}_{s,p}$ are the result from the inverter input to the ram position x respectively the hydraulic pressure p. The matrices describe the system input-output behaviour along the desired trajectory:

$$\underline{x}_{j+1} = \underline{M}_{s,x} \cdot \underline{u}_{j+1} \qquad \text{and} \qquad \underline{p}_{j+1} = \underline{M}_{s,p} \cdot \underline{u}_{j+1} \tag{9}$$

The feedforward signal for the next trial $\underline{u}_{j+1}$ is calculated via

$$\underline{u}_{j+1} = \underline{u}_j + \eta \cdot \underline{g}_j. \tag{10}$$

The next step is the substitution of equation (10) into (9) and (5). The error in the next cycle (equation (3)) can be expressed with the aid of equation (9) only by variables of the actual cycle j. After inserting equations (3) and (5) into (7), the cost criterion J_{j+1} only depends on the desired trajectories $\underline{w}_x$ and $\underline{w}_p$, the feedforward signal of the actual trial $\underline{u}_j$ and the learning function $\underline{g}_j$. The learning gain η is set to one and finally the new cost criterion (11) for the minimum search is the result.

$$\begin{aligned} J_{j+1} = &\left(\underline{w}_x - \underline{M}_{s,x} \cdot \underline{u}_j - \underline{M}_{s,x} \cdot \underline{g}_j\right)^T \cdot \underline{Q}_x \cdot \left(\underline{w}_x - \underline{M}_{s,x} \cdot \underline{u}_j - \underline{M}_{s,x} \cdot \underline{g}_j\right) \\ &+ \left(\underline{w}_p - \underline{M}_{s,p} \cdot \underline{u}_j - \underline{M}_{s,p} \cdot \underline{g}_j\right)^T \cdot \underline{Q}_p \cdot \left(\underline{w}_p - \underline{M}_{s,p} \cdot \underline{u}_j - \underline{M}_{s,p} \cdot \underline{g}_j\right) \\ &+ \left(\underline{M}_\Delta \cdot \underline{u}_j + \underline{M}_\Delta \cdot \underline{g}_j\right)^T \cdot \underline{Q}_u \cdot \left(\underline{M}_\Delta \cdot \underline{u}_j + \underline{M}_\Delta \cdot \underline{g}_j\right) \end{aligned} \tag{11}$$

Minimizing the cost criterion in equation (11) with respect to $\underline{g}_j$

$$\min_{\underline{g}_j}\{J_{j+1}\} = \frac{\partial J_{j+1}}{\partial \underline{g}_j} = 0 \tag{12}$$

yields to the optimal learning function

$$\underline{g}_j = \underline{M}_1 \cdot \left(\underline{w}_x - \underline{y}_{x,j}\right) + \underline{M}_2 \cdot \left(\underline{w}_p - \underline{y}_{p,j}\right) - \underline{M}_3 \cdot \underline{\Delta u}_j \tag{13}$$

with

$$\begin{aligned} \underline{M}_1 &= \left(\underline{M}_{s,x}^T \cdot \underline{Q}_x \cdot \underline{M}_{s,x} + \underline{M}_{s,p}^T \cdot \underline{Q}_p \cdot \underline{M}_{s,p} + \underline{M}_\Delta^T \cdot \underline{Q}_u \cdot \underline{M}_\Delta\right)^{-1} \cdot \underline{M}_{s,x}^T \cdot \underline{Q}_x \\ \underline{M}_2 &= \left(\underline{M}_{s,x}^T \cdot \underline{Q}_x \cdot \underline{M}_{s,x} + \underline{M}_{s,p}^T \cdot \underline{Q}_p \cdot \underline{M}_{s,p} + \underline{M}_\Delta^T \cdot \underline{Q}_u \cdot \underline{M}_\Delta\right)^{-1} \cdot \underline{M}_{s,p}^T \cdot \underline{Q}_p \\ \underline{M}_3 &= \left(\underline{M}_{s,x}^T \cdot \underline{Q}_x \cdot \underline{M}_{s,x} + \underline{M}_{s,p}^T \cdot \underline{Q}_p \cdot \underline{M}_{s,p} + \underline{M}_\Delta^T \cdot \underline{Q}_u \cdot \underline{M}_\Delta\right)^{-1} \cdot \underline{M}_\Delta^T \cdot \underline{Q}_u \end{aligned} \tag{14}$$

The feedforward signal for the next trial can now be computed by substituting equation (13) into (10).

4. Injection Moulding Model

As mentioned in chapters 1 and 3, the model-type ILC needs a model of the system dynamics to update the feedforward signal. Consequently, the creation of a mathematical description of the injection unit is required. This was done by Heilmann /8/ in his diploma thesis, based on the development environment MATLAB/Simulink. The model structure is shown in **Figure 4**.

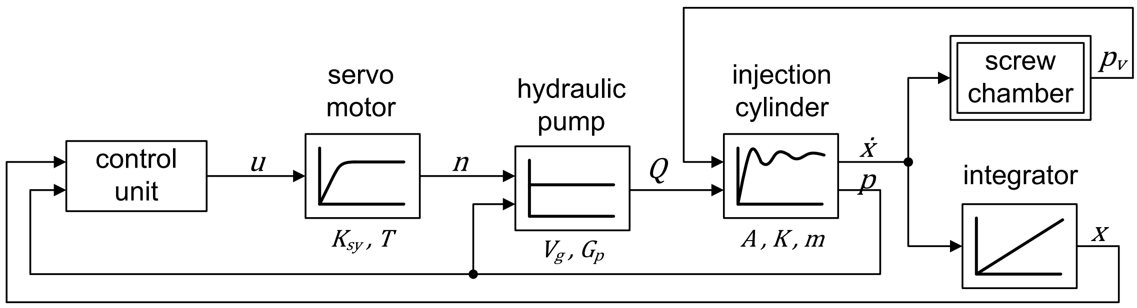

Figure 4: Block diagram of the injection unit

The injection unit is a displacement-controlled hydraulic drive system, consisting of a frequency inverter with servo motor driving a constant pump. The injection ram is moved by two differential cylinders and injects the hot plasticized polymer into the mould.

Motor and inverter are modelled as a PT_1 element with speed-dependent motor time constant $T(n)$ and the transmission gain K_{sy}. The motor speed is calculated as follows.

$$\frac{dn}{dt} = \frac{K_{sy} \cdot u \ - \ n(t)}{T(n)} \tag{15}$$

The pump drives a proportional flow reduced by a pressure dependent leakage G_p.

$$Q(t) = \ V_g \cdot n(t) - G_p \cdot p_A(t) \tag{16}$$

Taking the bulk modulus K' into account, pressure build-up in volume V_A of the injection cylinder is considered as

$$\frac{dp_A}{dt} = \frac{K'}{V_A(t)} \cdot [Q(t) - A_A \cdot \dot{x}(t)] \tag{17}$$

together with the motion equation

$$\sum F = m \cdot \ddot{x}(\mathrm{t}) = \ p_A(\mathrm{t}) \cdot A_A - p_B(\mathrm{t}) \cdot A_B - F_L - F_R \tag{18}$$

The load force F_L can be ascribed to the pressure increase in the area in front of the screw. The frictional force F_R represents the sum of the frictional forces in the injection cylinder and the viscous friction of the melt. The pressure build-up in front of the screw is modelled in the block “screw chamber” in Figure 4. The transfer behaviour is nonlinear and depends on the used mould. For detailed information, please refer to Heilmann /8/. The simulation model calculates the hydraulic pressure p and the ram position x at the output. The control strategy is a switched control, which has a separate controller for each phase and is represented as the "control unit" block in Figure 4. During the injection phase, the ram position x is the relevant control variable and a proportional-type controller with gain $K_{p,x}$ is used to stabilize the process. When the prescribed hydraulic pressure level is reached, the hydraulic pressure p becomes the relevant control variable. Therefore, the proportional-type controller with gain $K_{p,p}$ for the packing phase is enabled.

The parameters of the machine simulation model are taken from Helbig /9/ and are shown in **Table 1** below.

area of the piston in chamber A	A_A	$7461{,}1 mm^2$
area of the piston in chamber B	A_B	$922{,}8 mm^2$
leakage of the displacement pump	G_p	$9.3 \cdot 10^{-12}\, {m^5}/{Ns}$
bulk modulus	K'	$6 \cdot 10^3 bar$
transmission gain servo motor	K_{sy}	$4{,}16\, {1}/{Vs}$
mass at the injection cylinder	m	$150 kg$
displacement volume pump	V_g	$50{,}6 cm^3$

Table 1: Parameters of the simulation model

5. Simulation Results

The simulations are carried out with MATLAB/Simulink using a sampling rate of $T_a = 1ms$. The injection velocity and pressure-trajectory are adjusted according to the manufacturer of the mould of the technical part which will be used for the performance test at the real machine later on. The desired trajectories for the ram position and the hydraulic pressure are shown in Figure 2. The desired ram position trajectory is a ramp with a slope of $\dot{x} = 55\, {mm}/{s}$. The desired hydraulic pressure trajectory has a staircase-shaped characteristic. The switching point in this application was set to $sp = 77\ bar$, which is 80% of the hydraulic pressure level after the switching point and is indicated by circles in the following figures. The parameters for the feedback controller $K_{p,x} = 90$ and $K_{p,p} = 10$ are selected in such way, that the closed-loop during the cycle is stable. To get a smooth transition at the switching point and a relatively low error level the weighting factors are set to $q_u = 1e^{-6},\ q_x = 1,\ q_p = 0.1$. The learning gain is set to $\eta = 0.15$ for high robustness. The simulation was repeated

100 times. **Figure 5** shows the desired and the simulated output values for the ram position before reaching the switching point sp and the load pressure value afterwards. The error is pictured under each plot.

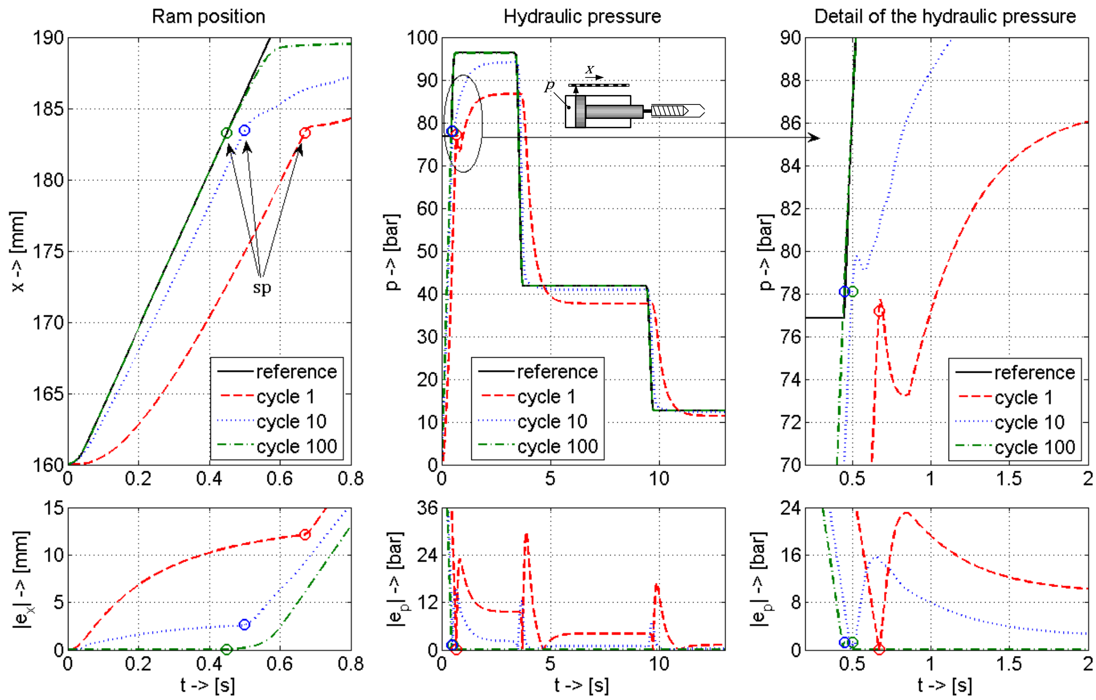

Figure 5: Ram position (left), hydraulic pressure (centre) and the hydraulic pressure at the transition in detail (right) of the simulation

In the first cycle only a smoothly parameterized P-type feedback controller was applied. Executing the ILC algorithm, the error decreases from cycle to cycle and the error is reducing to a maximum of $e_{x,max} = 0{,}1mm$ in position and $e_{p,max} = 1bar$ in pressure. This result is achieved after the 45th cycle. From then on, the ILC runs stably and no betterment process can be observed. The exponential decreasing level of the sums of squared errors are shown in **Figure 7** with

$$J_{ex,j} = \underline{e}_{x,j}^T \cdot \underline{Q}_x \cdot \underline{e}_{x,j} \qquad \text{and} \qquad J_{ep,j} = \underline{e}_{p,j}^T \cdot \underline{Q}_p \cdot \underline{e}_{p,j} \tag{19}$$

6. Performance Test

The ILC was applied to an injection moulding machine at the TU Dresden Institute of Fluid Power. Parameterization and reference trajectories are the same as in chapter 5. The process control is executed by using a dSPACE real-time system connected to a PC. Results for the ram position and the hydraulic pressure are shown in **Figure 6**.

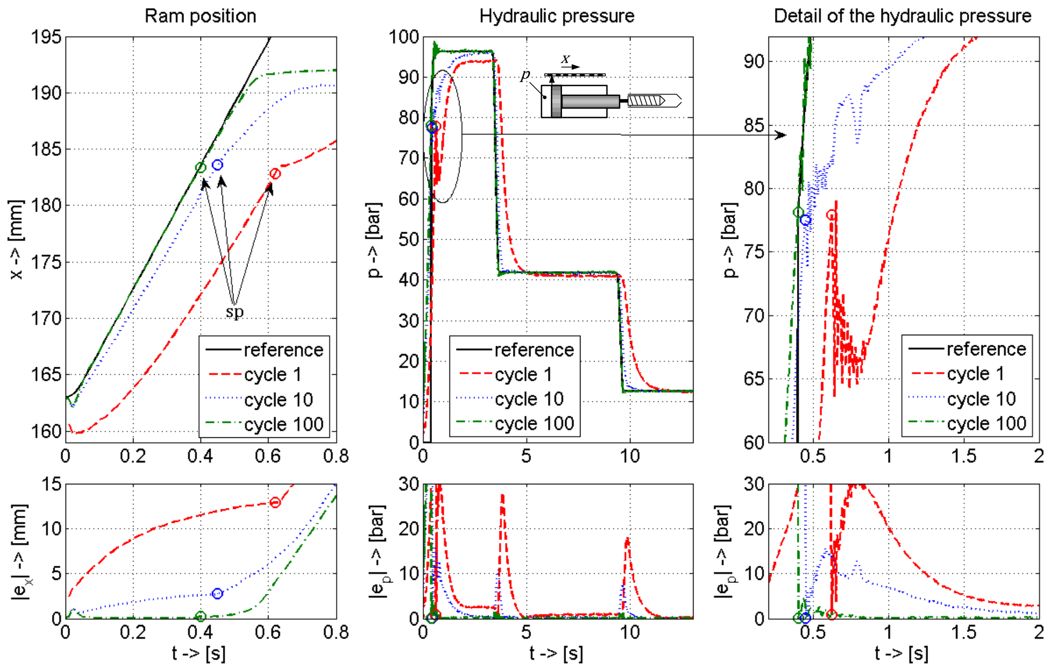

Figure 6: Ram position (left), hydraulic pressure (centre) and the hydraulic pressure at the transition in detail (right) at the actual machine

The hydraulic pressure in the injection moulding machine at cycle 100 followed the desired trajectory closely. Small oscillations in the system pressure occurred as responses to the given pressure steps. The sums of squared errors show a stable exponential learning rate in accordance with the simulation. The prediction of the learning rate worked properly.

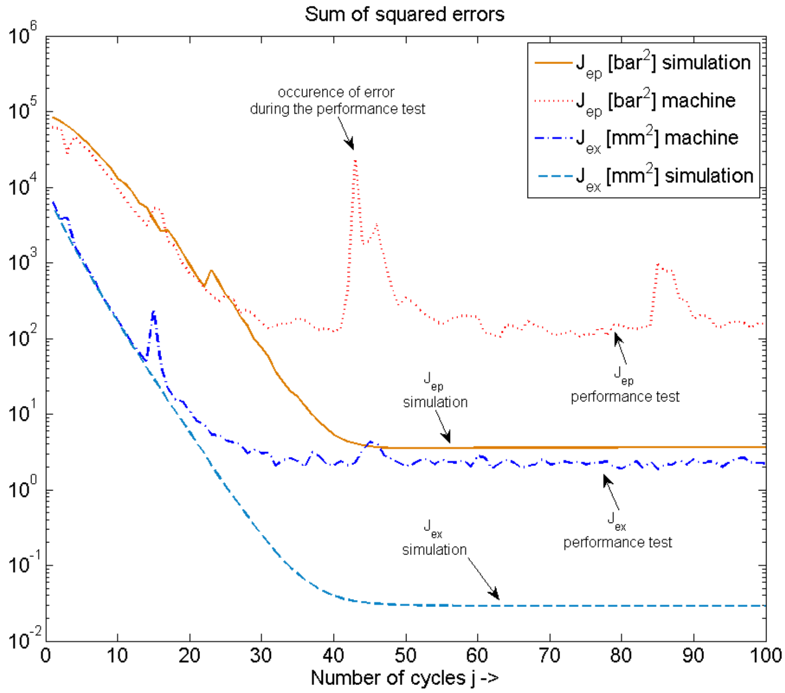

Figure 7: Sum of squared errors in simulation and at the actual machine

An example for the disturbance-flexibility of the algorithm can be seen at the 45th cycle, when a frozen sprue blocks the nozzle and prevents an injection. After the blockage is eliminated, the algorithm decreases the pressure error cycle by cycle until the pre-disturbance error level is reached once again. However, compared to the simulation, the minimum of the sum of squared errors at the actual machine is approximately two decades higher. This is caused by the simplicity of the model, which only takes into account the major nonlinearities and the fact that the measured sensor-signals are naturally noisy.

7. Conclusion

This paper has proposed the application of an iterative learning controller to the injection unit of an injection moulding machine. It has been shown, that the controller achieves a good tracking performance and is robust to the influence of external disturbances. A switching-law eliminates the overshoot between the injection and packing phase which is a requirement for a stable production quality. Furthermore, the controller acts stably when errors occur - even though the underlying model is quite simple. As the iterative learning controller does not influence the closed-loop stability, the feedback controller can be designed as a disturbance compensator. Displacement-controlled systems with variable speed pumps are an energy-efficient alternative to valve-controlled drives, but because of their big inertia they tend to be less dynamic. Moreover, today's controllers often cannot recall maximum dynamics due to stability reasons. In contrast to this, the learning controller is able to take advantage of the strength of this driving concept by exploiting the maximum dynamics.

Yet, further investigations regarding the limitations of the drive-systems and the error handling need to be carried out.

8. Acknowledgment

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Nomenclature

n	motor speed	$1\ /\ \mathrm{min}$
p	hydraulic pressure	bar
p_v	melt pressure in front of the screw	bar
Q	hydraulic flow	$\mathrm{m^3/s}$
T	motor time constant	s
u	input signal	$1/\mathrm{min}$
V	volume of the injection cylinder	$\mathrm{m^3}$
x	ram position	mm
$\dot{x}$	ram velocity	$\mathrm{mm/s}$
$\ddot{x}$	ram acceleration	$\mathrm{mm/s^2}$