Dynamic improvement of hydraulic drive trains by trajectory planning and learning algorithms

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Abstract

The improvement of servo-controlled applications and the disturbance-compensation with good dynamics, little overshooting and minimization of steady state errors is a focus of investigation in electrohydraulic drive trains. The need for energy-saving solutions with good efficiency leads to the question how the productivity of drive trains can be maximized. The approach proposed in this paper shows a way to maximize the utilization of repetitive processes taking the drive limitations into account. Combining the planning of trajectories according to the systems limitations and an iterative learning controller (ILC) this paper shows a way to achieve good accuracy despite varying drive system parameters and limitations. The iterative approach uses an inversion-based mathematical model of a highly nonlinear plant to minimize the position error on basis of a quadratic next-iteration cost criterion. To show the potential of the ILC it is applied to the displacement-controlled clamping unit of a 1600 kN injection moulding machine. Furthermore the methodology shows a way to recall the maximum dynamic potential of the displacement-controlled hydraulic drive system without reaching stability limits.

Keywords: iterative learning control, ILC, trajectory planning, injection moulding, energy efficiency, drive constraints.

1. Introduction

Energy-saving drive trains play a major role in research and development. Especially in stationery machinery there is a huge potential for energy-saving drive trains, which the developments during the last ten years show. Many tests have been carried out to compare dynamic performance, price and efficiency. However, these comparisons especially between hydraulic and electromechanic market-available drive trains often did not account for the fact that the overall efficiency of drive trains highly depends on the operating point.

If big forces need to be applied with excellent dynamic performance, hydraulic valve control is the drive of choice. New concepts with separated meter-in meter-out valves improve the situation but throttle losses still limit the efficiency. Servo-driven displacement controlled systems have been investigated for a long time /1/,/2/ and are nowadays applied in a lot of machines. However, maximum dynamics are often not recalled because of stability problems and improvements being made based on experience as well as “trial and error”.

Plastics and rubber machinery is one of the most important fields of series machines in which hydraulic drive systems are applied. Driven by the trend of falling prices in electric servodrive technology and the demand for energy-saving drive trains, displacement-controlled drives have gained importance in stationary machinery. The fact that in many industrial applications the requirements are not exactly known results in oversized components and hence a lower grade of utilization and higher capital cost. Many studies have been carried out in the last years to strengthen the position of hydraulics in this highly competitive market via the integration of modern control strategies. Apart from the improvement of the process itself, the decrease of cycle times is one key to increase efficiency. For existing systems the best productivity can be reached if the systems are used to full capacity, this also applies to the drive trains themselves. In the case of follow-up control systems this results in the need for a trajectory which uses the system to full capacity.

In a previous paper /3/ it was shown how a trajectory planning in combination with a feed-forward control based on the inversion of the system can improve the tracking performance significantly. One remaining challenge is that the tracking performance directly depends on the model accuracy. As a consequence errors in the system description and time related parameter changes can only be reduced by a closed-loop control which again leads to compromises of reference and fault-response action. Promising closed-loop control concepts such as input-output linearization or sliding-mode control have been applied to hydraulic drives during the last years /4/,/5/,/6/. These advanced controllers use the knowledge of the plant to act against an (already occurred) error. If the process and even the trajectory are known one can use these facts to overcome this structural problem of online closed-loop control. Iterative learning control (ILC) is a promising offline control scheme for repetitive processes as it offers the chance to incorporate past control information. Problems occur if due to model inaccuracies or changing parameters drive limitations are reached: Tracking errors increase and ILC may become instable.

The paper focuses on a systematic approach to increase the usage of an energy-saving servo-driven displacement controlled clamping unit of an injection moulding machine and is outlined as follows: In chapter 2 an analytical description of the system is derived. It is used in chapter 3 for deriving trajectories in order to exploit the maximum dynamics of the system and to provide an analytical description of a model-based feed-forward control. In chapter 4 the iterative learning law is introduced and expanded by the consideration of the systems limitations. Chapter 5 presents results of the practical implementation. Finally, chapter 6 concludes by summing up the results and giving an outlook on further investigations.

2. Process and drive system description

The injection moulding process is a discontinuous primary shaping procedure. An injection moulding machine (IMM) consists of different drive systems which realize the movements for a stable plastic injection moulding process. The clamping unit drive system operates the opening and closing of the mould and applies the clamping force. A toggle lever system features a highly nonlinear transmission ratio and is therefore often used for high performance machines. Here the movement and clamping of the mould makes up to 40% of the process-time, wherefore a shortening directly leads to an increase of productivity. **Figure 1** shows the clamping unit used for the investigations.

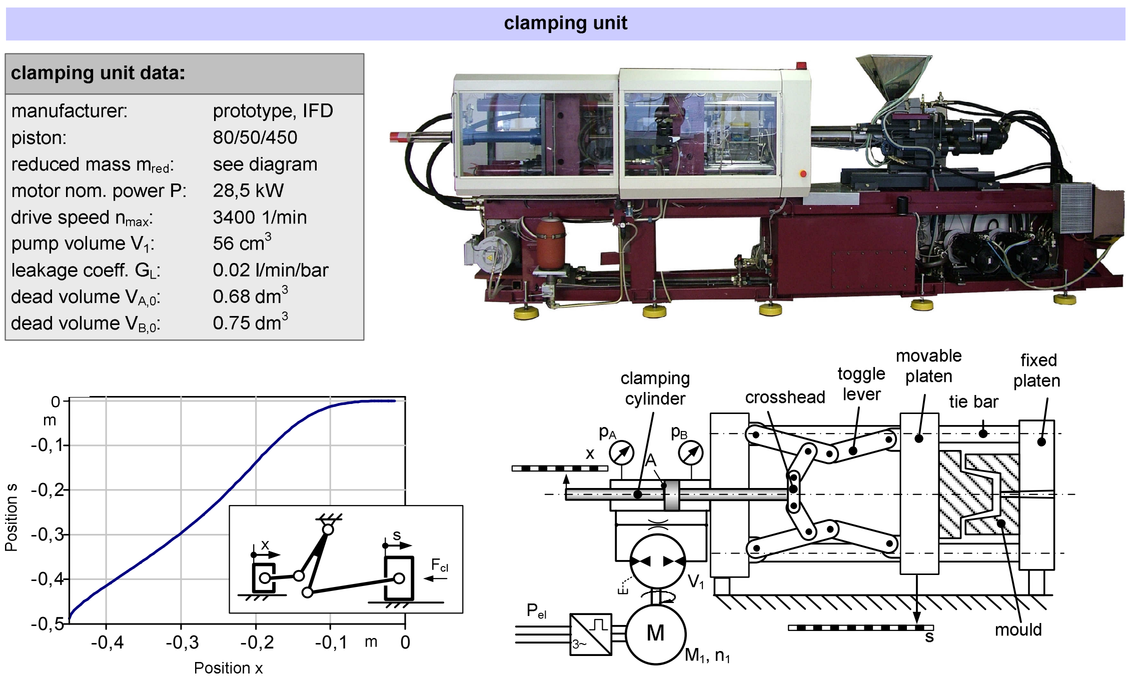

Figure 1: Injection moulding machine and clamping unit structure

The drive system structure consists of a combination of electric, hydraulic and mechanical parts. A model covering the main influencing effects requires mathematical descriptions of frequency inverter and motor,

$$\dot{n} = \frac{K \cdot u - n}{T_1(n)} \tag{1}$$

the hydraulic pump,

$$Q_1 = V_1 \cdot n\,, \tag{2}$$

continuity equation and pressure build-up in the double-rod cylinder,

$$p_L = p_A - p_B\,, \tag{3}$$

$$\dot{p}_L = \frac{1}{C_h(x)}\left[n \cdot V_1 - A \cdot \dot{x} - G_L \cdot p_L\right], \tag{4}$$

as well as the equilibrium of forces /7/:

$$m(x) \cdot \ddot{x} = (p_A - p_B) \cdot A - k_d(x) \cdot \dot{x} - (F_C(x) + F_L(x)). \tag{5}$$

Transforming these equations in the complex variable domain yields the transfer function:

$$G(s) = \frac{x}{u} = \frac{b_0}{a_1 \cdot s + a_2 \cdot s^2 + a_3 \cdot s^3 + a_4 \cdot s^4} \tag{6}$$

with the coefficients

$$b_0 = A \cdot K \cdot V_1 \tag{7}$$

$$a_1 = G_L \cdot k_d(x) \cdot A^2 \tag{8}$$

$$a_2 = T_1(n) \cdot \left(G_L \cdot k_d(x) + A^2\right) + \left(C_h(x) \cdot k_d(x) + G_L \cdot m(x)\right) \tag{9}$$

$$a_3 = T_1(n) \cdot \left(C_h(x) \cdot k_d(x) + G_L \cdot m(x)\right) + C_h(x) \cdot m(x) \tag{10}$$

$$a_4 = T_1(n) \cdot C_h(x) \cdot m(x) \tag{11}$$

and the nonlinearities shown in **figure 2**. For a detailed derivation we refer to /3/ and /8/.

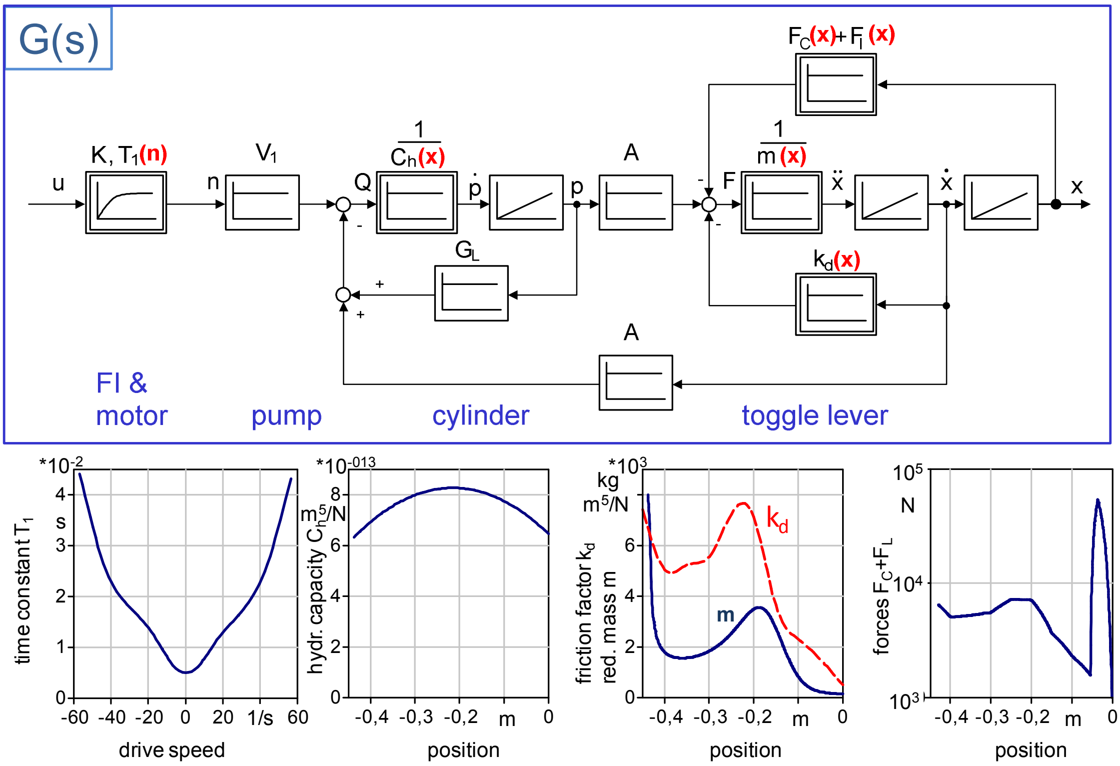

Figure 2: Nonlinear system structure

At this point, the model can be validated comparing the transient response of the model with the real system, **figure 3**.

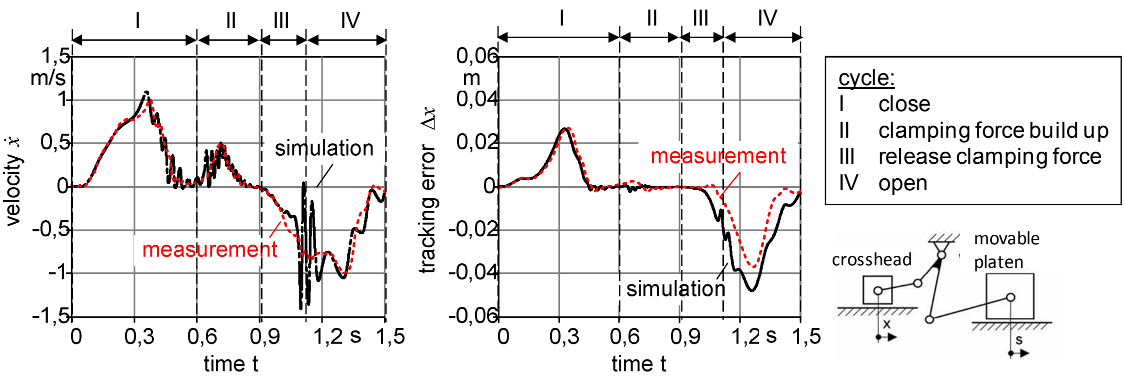

Figure 3: Simulation and measurement of tracking error and velocity

3. Control structure

To reach maximum dynamics with the best tracking performance possible, a motion path (trajectory) has to be created considering the constraints given by the physical system structure. The tracking error can be kept small with a model-based feed-forward control. The open-loop control is closed by a proportional controller.

3.1. Trajectory generation

The idea of a model-based trajectory generation is to account for the inherent physical system boundaries (e.g. maximum motor torque, limitations of speed, acceleration and jerk, temperature…) and the user-given boundaries (i.e. speed limits or tracking performance because of a manufacturing process) while planning a motion track. This leads to a trajectory which drives the system as close as possible along the inherent boundaries. A convenient way to derive the shortest possible trajectory is to calculate the path along the given restrictions of motor torque, speed and jerk. In this work an iterative calculation along the given boundaries is proposed, calculating the shortest possible time step for the next position step dx of the discretised trajectory:

$$x_{i+1} = x_i + dx \tag{12}$$

Starting from a certain point x_0 the time Δt of the next interval dx can be derived iteratively using the maximum allowed jerk $\dddot{x}_{\max}$ as equation 13 illustrates.

$$dx = \frac{1}{6}\dddot{x}_{\max} \cdot \Delta t^3 + \frac{1}{2} \cdot \ddot{x}_{i-1} \cdot \Delta t^2 + \dot{x}_{i-1} \cdot \Delta t \tag{13}$$

Now we need to check if the calculated time Δt exceeds the maximum acceleration and/or speed. This is done via

$$\ddot{x}_i = \begin{cases} \dddot{x}_{\max} \cdot \Delta t + \ddot{x}_{i-1} & ,if\ \ddot{x}_i < \ddot{x}_{\max} \\ \ddot{x}_{\max} & elseif \end{cases} \tag{14}$$

$$\dot{x}_i = \begin{cases} \frac{1}{2}\dddot{x}_{\max} \cdot \Delta t^2 + \ddot{x}_{i-1} \cdot \Delta t + \dot{x}_{i-1} & ,if\ \dot{x}_i < \dot{x}_{\max} \\ \dot{x}_{\max} & elseif \end{cases} \tag{15}$$

Applying this calculus iteratively to each step of the calculation, a trajectory, which meets one of the given boundaries in each point, can be derived piecewise. The resulting track is interpolated with b-splines to assure a continuous differentiable motion trajectory.

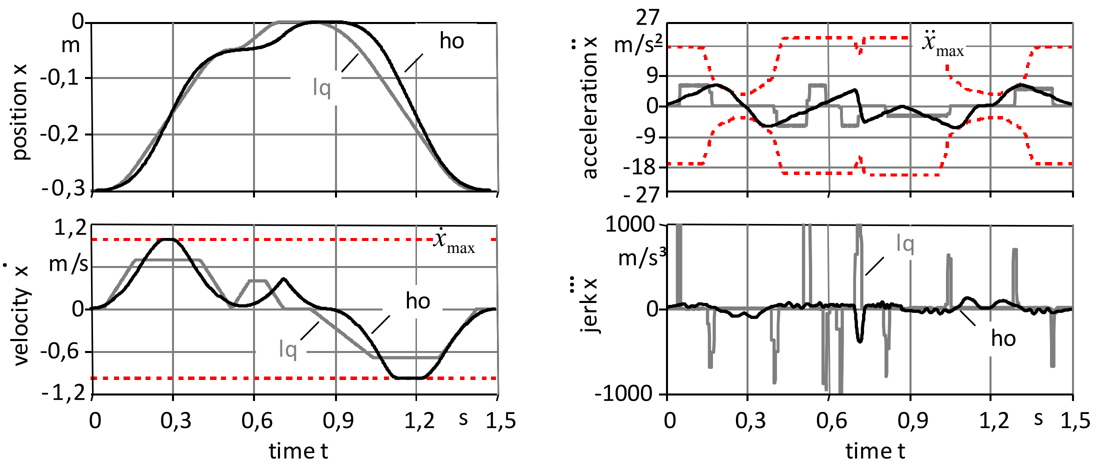

Figure 4: Linear quadratic trajectory of an industrial controller (lq) and developed higher order trajectory (ho)

Figure 4 illustrates the difference between the higher order (ho) and a linear quadratic (lq) motion preset: the constraints of the drive train (marked in red, dashed) are used and the jerk, which causes an excitation of the plant, is reduced. This leads to higher possible dynamics.

3.2. Feed-forward and closed-loop control

A model-based feed-forward control structure allows for reduction of tracking errors without having an influence on the stability. An inverse feed-forward control leads to small error - in case of an ideal model to zero tracking error. The inverse of the transfer function (6)

$$u(s) = \frac{x(s)}{b_0} \cdot \left(a_4 \cdot s^4 + a_3 \cdot s^3 + a_2 \cdot s^2 + a_1 \cdot s\right) \tag{16}$$

can be transformed into time domain. This leads to the feed-forward law:

$$u^*(t) = \frac{1}{b_0}\left[a_4 \cdot \frac{d^4x(t)}{dt^4} + a_3 \frac{d^3x(t)}{dt^3} + a_2 \cdot \frac{d^2x(t)}{dt^2} + a_1 \cdot \frac{d\ x(t)}{dt}\right]. \tag{17}$$

The better the system description matches the real plant and the less distorsions appear, the smaller is the tracking error.

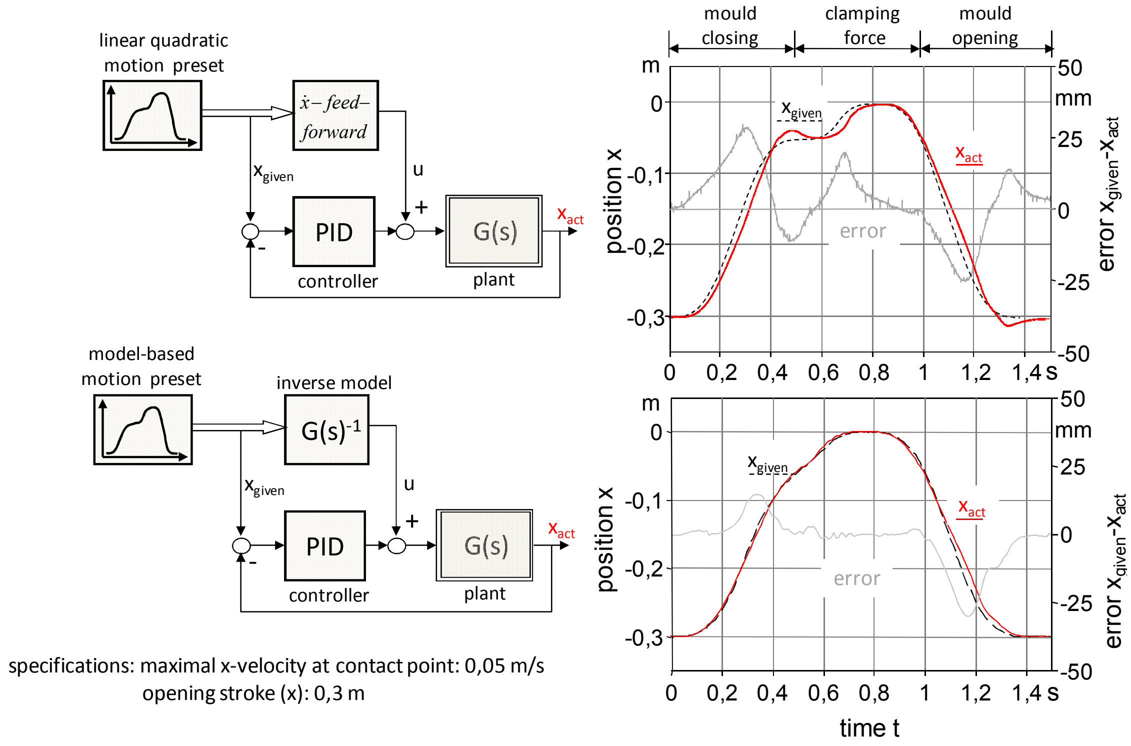

Figure 5: Results of different control structures

As mismatches occur due to the inaccuracy of the model and parameter changes, a closed-loop controller is needed in order to reduce the error further. Even though closed-loop control structures differ in complexity, the structural problem of remains: The feedback controller cannot anticipate the error. Even though there are many promising algorithms, the simplicity of tuning makes PID-control remaining the standard control in industrial applications. In the following section we show how an iterative learning (open-loop) controller can reduce the tracking error. A proportional controller is introduced as example for a closed-loop control.

4. Iterative learning control

The idea of ILC goes back to 1967 when Garden /9/ filed the first patent on learning control. Independently of him, Arimoto independently developed an ILC in 1984 /10/. Iterative control schemes can be classified into two different classes depending the use of the model information /11/: Gain-type ILC process the feed-forward signal on the basis of linear operations on the error without taking the system dynamics into account. This yields convergence if the gain is properly chosen. Model-type ILC was introduced by Amann /12/ and makes use of an a priori known system dynamics which results in rapidly converging solutions with less parameterization effort. Unfortunately the "inverse problem" has to be solved, which, depending on the system may be ill-posed.

Several investigations have been carried out with the aim to implement ILC algorithms on stationary machinery, in particular on injection moulding machines. Havlicek and Alleyne /13/ were the first who applied an iterative control algorithm to an injection moulding machine (IMM). They applied a gain-type ILC to the injection unit of an injection moulding machine that resulted in an improved tracking control compared to a conventional PI-controller. Gao, Yang and Shao /14/ applied a model-type ILC to an IMM using a model derived from open-loop step answer identification. They achieved good results by varying the error-weighting matrices. Dynamic restrictions of the process have not been taken into account.

The presented ILC shows how the usage of a displacement-controlled clamping unit can be improved using a trajectory planning in combination with a model-based feed-forward control and the ILC algorithm proposed by Amann /12/. The latter is extended considering the saturation of the control signal.

4.1. Learning law

In chapter 3 we derived a control structure based on the system description in chapter 2. In the ideal case of an exact inversion $\underline{G}_S^{-1}$ of the nonlinear plant a feed-forward signal $\underline{u} = \underline{w} \cdot \underline{G}_S^{-1}$ can be derived for a given trajectory $\underline{w}^{(N\times 1)}$. In this case there is no tracking error ($\underline{x} \equiv \underline{w}$). Due to the inexact description of the system the inversion $\underline{G}_S^{*-1}$ leads to a non-ideal feed-forward signal $\underline{u}^* = \underline{w} \cdot \underline{G}_S^{*-1}$ for the first cycle and a nonzero tracking error:

$$\underline{e} = \underline{w} - \underline{u}^* \cdot \underline{G}_S = \underline{w} - \underline{x} \neq 0 \qquad (18)$$

Figure 6 shows a scheme of the ILC applied to the plant.

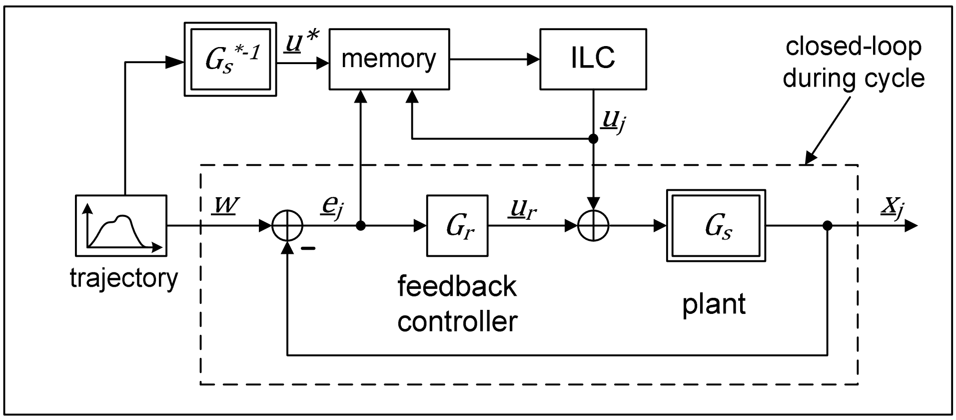

Figure 6: Control structure with ILC and closed-loop control

We will reduce the tracking error $\underline{e}^{(N\times 1)}$ consecutively by iterative learning. To do so, we calculate the feed-forward signal of the next cycle according to

$$\underline{u}_{j+1} = \underline{u}_j + \eta \cdot \underline{\Delta u}_{j+1} \tag{19}$$

with the learning factor η and $\underline{\Delta u}_{j+1}$. The latter represents an unknown supplement which minimizes the error $\underline{e}$. We assume $\underline{e}$ to be small; consequently it can be described by a linear transfer function in time domain by a linearization of the greatly nonlinear plant along the path using the lifted system representation /15/:

$$\underbrace{\begin{bmatrix} x_{j+1}(0) \\ x_{j+1}(1) \\ x_{j+1}(2) \\ \vdots \\ x_{j+1}(N) \end{bmatrix}}_{\underline{x}_{j+1}} \approx \underline{u}_j \cdot \underline{G}_S + \underbrace{\begin{bmatrix} f_s(0,0) & 0 & 0 & \cdots & 0 \\ f_s(1,0) & f_s(1,1) & 0 & \cdots & 0 \\ f_s(2,0) & f_s(2,1) & f_s(2,2) & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_s(N,0) & f_s(N,1) & f_s(N,2) & \cdots & f_s(N,N) \end{bmatrix}}_{\underline{M}_s} \cdot \underbrace{\begin{bmatrix} \Delta u_{j+1}(0) \\ \Delta u_{j+1}(1) \\ \Delta u_{j+1}(2) \\ \vdots \\ \Delta u_{j+1}(N) \end{bmatrix}}_{\underline{\Delta u}_j+1} \tag{20}$$

whereby the lifted system matrix $\underline{M}_s$ contains the time-variable impulse responses $f_s(k,l)$ with $0 \le k \le l \le N$. k indicates the discrete time step of each impulse response and l the starting time step. The impulse responses are created for the closed-loop simulation model in figure 6.

The supplement $\underline{\Delta u}_{j+1}$ is to be calculated on the basis of a cost criterion J so that

$$\min_{\underline{\Delta u}_{j+1}} \{J_{j+1}\} = \frac{\partial J_{j+1}}{\partial \underline{\Delta u}_{j+1}} = 0 \tag{21}$$

For the clamping unit of the injection moulding machine the new tracking error $\underline{e} - \underline{M}_s \cdot \underline{\Delta u}_{j+1}$ has to be minimized. Hereby $\left\| \underline{u}_j + \underline{\Delta u}_{j+1} \right\|_2$ minimizes the control signal and $\left\| \underline{\Delta u}_{j+1} \right\|_2$ guarantees that the minimum is unique. Saturation constraints of the feed-forward signal are considered by $\left\| \underline{u}_j + \underline{\Delta u}_{j+1} - \underline{u_B}_j \right\|_2$ where $\underline{u_B}_j$ is the constrained signal of $\underline{u}_j$. This leads to the optimality-criterion

$$\begin{aligned} J_{j+1} = {} & \left\| \underline{e}_j - \underline{M}_s \cdot \underline{\Delta u}_{j+1} \right\|_2 + q_1 \cdot \left\| \underline{u}_j + \underline{\Delta u}_{j+1} \right\|_2 + \\ & + q_2 \cdot \left\| \underline{\Delta u}_{j+1} \right\|_2 + q_3 \cdot \left\| \underline{u}_j + \underline{\Delta u}_{j+1} - \underline{u_B}_j \right\|_2 \end{aligned} \tag{22}$$

with the weighting-factors q_1, q_2, q_3 and the quadratic norm $\| \cdot \|_2$. In matrix formulation results

$$\begin{aligned} J_{j+1} = {} & \left(\underline{e}_j - \underline{M}_s \cdot \underline{\Delta u}_{j+1} \right)^T \cdot \left(\underline{e}_j - \underline{M}_s \cdot \underline{\Delta u}_{j+1} \right) + \\ & + \left(\underline{u}_j + \underline{\Delta u}_{j+1} \right)^T \cdot \underline{Q}_1 \cdot \left(\underline{u}_j + \underline{\Delta u}_{j+1} \right) + \underline{\Delta u}_{j+1}{}^T \cdot \underline{Q}_2 \cdot \underline{\Delta u}_{j+1} + \\ & + \left(\underline{u}_j + \underline{\Delta u}_{j+1} - \underline{u_B}_j \right)^T \cdot \underline{Q}_3 \cdot \left(\underline{u}_j + \underline{\Delta u}_{j+1} - \underline{u_B}_j \right) \end{aligned} \tag{23}$$

with the weighting matrices $\underline{Q}_i = q_i \cdot \underline{E}$ with the unit matrix $\underline{E}_{m,n} = \begin{cases} 1, \; if\; m = n \\ 0, \; elseif \end{cases}$

Setting the derivative to zero leads to:

$$\begin{aligned} &-2 \cdot \left(\underline{e}_j - \underline{M}_s \cdot \underline{\Delta u}_{j+1}\right)^T \cdot \underline{M}_s + 2 \cdot \left(\underline{u}_j + \underline{\Delta u}_{j+1}\right)^T \cdot \underline{Q}_1^{\,T} \\ &\quad + 2 \cdot \underline{\Delta u}_{j+1}^{\,T} \cdot \underline{Q}_2^{\,T} + 2 \cdot \left(\underline{u}_j - \underline{u}_{B_j} + \underline{\Delta u}_{j+1}\right)^T \cdot \underline{Q}_3^{\,T} = 0 \end{aligned} \tag{24}$$

If equation 24 is resolved by $\underline{\Delta u}_{j+1}$ this leads to the learning function:

$$\underline{\Delta u}_{j+1} = \left(\underline{M}_s^{\,T} \cdot \underline{M}_s + \underline{Q}_1 + \underline{Q}_2 + \underline{Q}_3\right)^{-1} \cdot \underline{M}_s^{\,T} \cdot \underline{e}_j - \underline{Q}_1 \cdot \underline{u}_j - \underline{Q}_3 \cdot \underline{u}_j + \underline{Q}_3 \cdot \underline{u}_{B_j} \tag{25}$$

The feed-forward signal for the next cycle results from the substitution of (25) in (19).

5. Results

This chapter shows some results of the iterative learning controller applied to the 160 ton clamping unit of the injection moulding machine which is described in chapter 2. The tests are carried out on a prototype controlled by a dSPACE environment. The test cycle is a typical “dry-cycle”, as specified in EUROMAP6. The ILC calculation is performed with MATLAB in between the cycles. Model-based motion presets with different dynamics are examined with an open-loop iterative controller structure (Fig. 9, structure B) and compared to the results of a closed loop iterative structure without ILC.

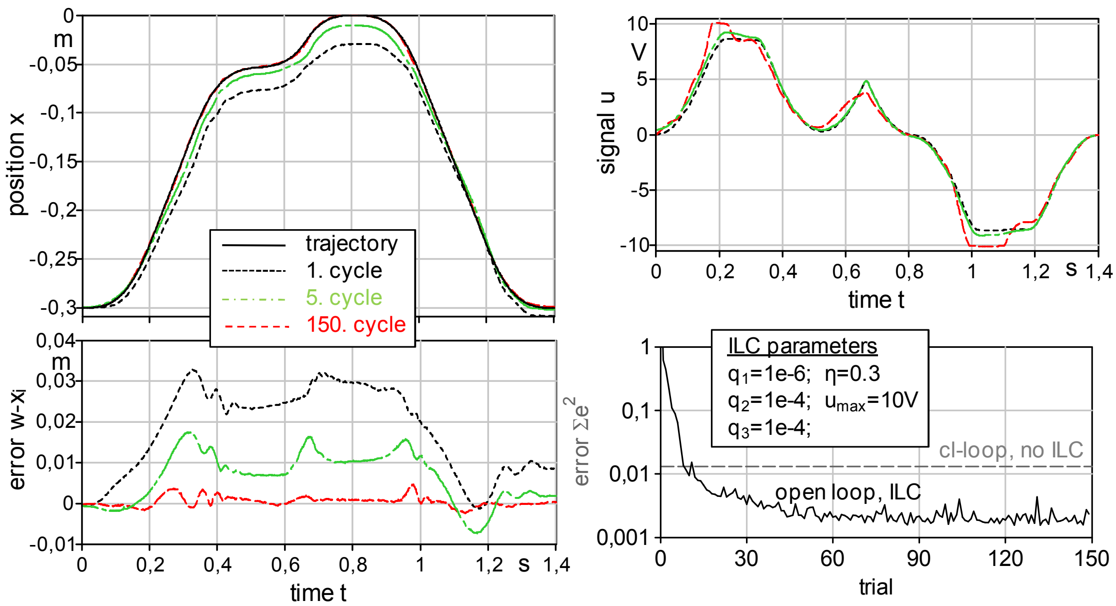

Figure 7: Results for 1.4s cycle (open-loop iterative control)

The iterative learning controller runs stably and reduces the integral position error more than 2 decades within 10 cycles. **Figure 7** shows the exponential reduction of the error over the cycles. Around the position of -0.1m the ILR is not able to reduce the oscillating error any further. On the one hand this is caused by the actuator which limits the plant input. On the other hand the bad damping in this area (see figure 2) and the changing eigenfrequency cause that the linearized model does mirror the real system accurately enough. The drive system's limitation of the drive system becomes even more obvious if the dynamic is increased any further.

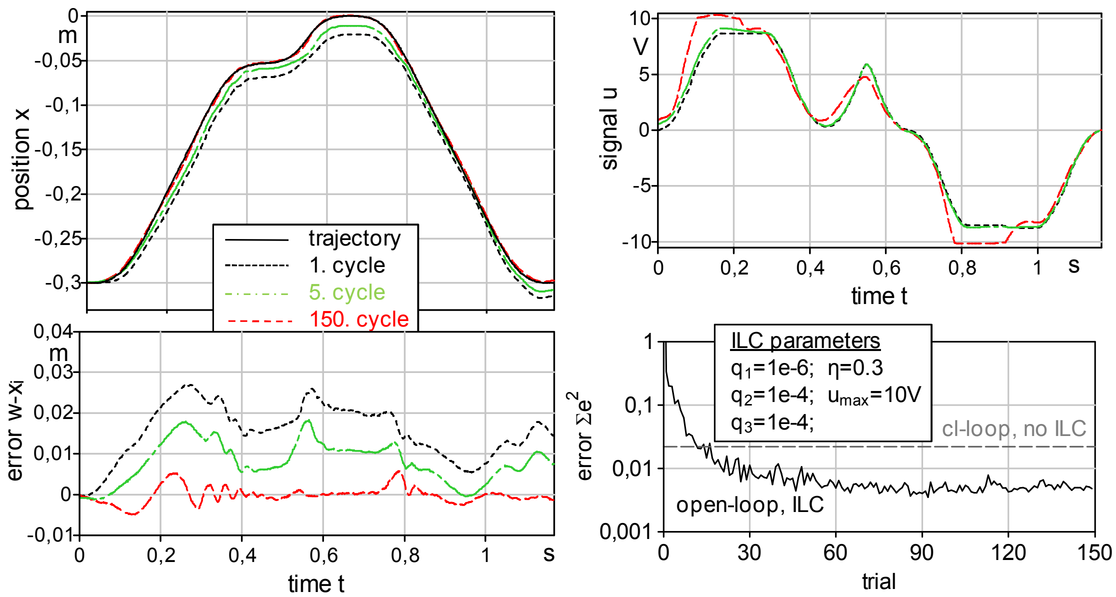

Figure 8: Results for 1.2s cycle (open-loop iterative control)

Figure 8 shows, that the controller runs stably despite not complying with the limit of $u_B = \pm 10V$. Here another challenge can be identified: A maximum utilisation criterion requires a trajectory-planning closest possible along the drive systems restrictions. In contrast to this an a priori unknown reserve for the control signal should be considered to overcome disturbances (e.g. wrongly estimated parameters or parameter changes).

A direct comparison of the two structures shows the potential of the iterative learning controller (**figure 9**).

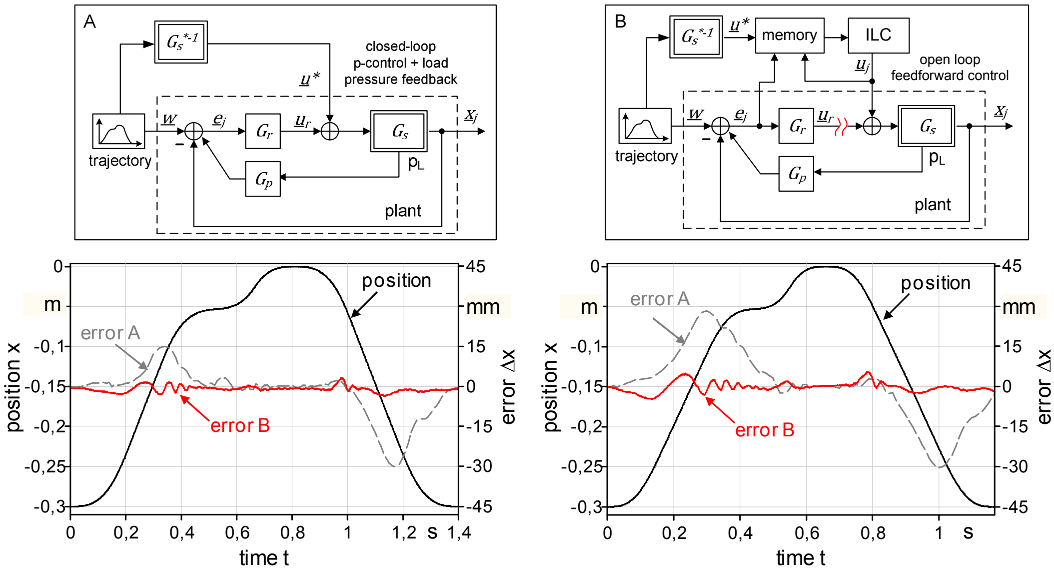

Figure 9: Comparison: closed-loop control (A) to ILC open-loop (B) for two different cycle times

6. Conclusion

An approach has been presented which shows the potential of a systematic, model-based approach to recall the maximal usage of a highly nonlinear plant that runs a repetitive process with a minimal error in order to avoid the struggle of tuning closed-loop controllers. Based on a mathematical description of the plant, motion presets are generated which lead to an increase of the system dynamics and illustrates why the "trial and error" method does not lead to the expected results. The improvement is realised without the use of additional components. Additionally it points out the bottlenecks.

A model-based open-loop iterative learning controller is presented that significantly reduces the absolute position error in comparison to similar closed-loop structure by using a standard proportional controller with load-pressure feedback. As the ILC works stably by definition it is able to recall the maximum dynamics in contrast to conventional controllers cannot due to stability reasons. Limiting factors are the systems limitations and the model accuracy which determine the residual error.

Issues persist, however with the accuracy of the model description particularly if small changes of given values cause model changes. As a consequence these cannot sufficiently be described by the linear supplement of the elevated system description. The challenge is to develop appropriate models with a good balance of complexity and accuracy.

Future work on learning controllers and the development of more sophisticated nonlinear control strategies is continuing.

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8. Nomenclature

A	area	m^2
a,b	coefficients	-
C_h	hydraulic capacity	m^5/N
e	error	m
F	force	N
G	plant description (time/ frequency domain)	
i,k,l	indices	-
J	optimisation functional	-
K	motor gain	1/Vs
k_d	friction coefficient	N
M	momentum	Nm
M_s	lifted system matrix	-
n	drive speed	1/s

p	pressure	bar, N/m^2
q, Q	weighting factor /matrix	
Q_1	pump flow	l/min, m^3/s
s	position (movable platen)	m
t	time	s
T_1	motor time constant	-
u	voltage	V
V_1	pump volume	dm^3, m^3
w	given trajectory	
x	position (crosshead)	m
η	learning factor	-