Introduction of Model Predictive Control for the System Optimization of a Proportional Directional Control Valve

Artemi Makarow, Jan Braun, Christoph Rösmann, Georg Schoppel, Ingo Glowatzky and Torsten Bertram

IEEE Conference on Control Technology and Applications (CCTA), Copenhagen, Denmark, 2018

Introduction of Model Predictive Control for the System Optimization of a Proportional Directional Control Valve

Artemi Makarow[1], Jan Braun[1], Christoph Rösmann[1], Georg Schoppel[2], Ingo Glowatzky[2] and Torsten Bertram[1]

***Abstract*— During a model-based system optimization of a proportional directional control valve, the system performance is simulated for a wide range of different design parameter sets. The behavior of the model, which is used to evaluate the system performance, changes whenever the optimization algorithm provides new parameter values. The closed-loop control response of a proportional valve is used as the metric of the system performance. Thus, to avoid evaluating the robustness of the valve controller, a new controller design is required whenever a variation of the plant parameters is carried out. The native controller of a proportional directional control valve is a nonlinear PID controller with numerous coupled parameters. This controller design requires a complex evolutionary multi-objective parameter optimization. This contribution introduces the model predictive control (MPC) in the context of a fully automated model-based system optimization of a proportional directional control valve. Since the plant is known exactly for every design variation, the plant model becomes a part of the control concept. By updating the prediction model, the controller exhibits a design adaptive characteristic. Due to the inherent system knowledge of the MPC setup within the model-based system optimization, the number of free controller parameters decreases significantly. These additional free parameters, like the weights of the user-defined objective function, can be included easily into the design optimization vector enabling a single holistic system optimization procedure.**

I. INTRODUCTION

A mechatronic system has different sub-systems from various domains. The interactions of these sub-systems during closed-loop control contribute to the system performance. However, usually, an almost serial and independent development process is performed. During a serial development, an attempt is made to improve the characteristics of the individual components. These might be, for instance, maximizing the force or torque and minimizing the friction. In the case of hydraulic valves, these subsystems are designed to reach the desired hydraulic characteristics of the whole system theoretically with consideration of safety aspects. The individual components are often developed using expert knowledge or domain-specific simulation approaches like the Finite-Element-Method (FEM) or the Computational Fluid Dynamics (CFD). After reaching a certain development status, the sub-systems are assembled to the whole mechatronic system. Then a suitable control concept is designed and the controller parameters are optimized to reach pre-defined performance requirements. The free controller parameters are optimized to achieve a high closed-loop performance and to overcome possible shortcomings of the individual sub-systems. The problems of the serial development process of mechatronic systems are discussed in [1] and [2]. The controller design according to pre-defined criteria is already a kind of system optimization. It enables the tuning of the system performance directly. In the case of hydraulic valves, the outer position controller is usually a complex nonlinear PID controller with plenty of coupled parameters to cover a wide operation range. A manual controller design, performed by a process expert, requires a high expenditure of time. For this reason, an automated evolutionary multi-objective Hardware-in-the-Loop (HiL) optimization procedure has been developed to reduce the optimization time [3].

To optimize the hardware design of a mechatronic system time- and cost-efficiently, a model-based development is needed. A suitable model should meet several requirements like a high simulation quality and a low computational effort to make a holistic system optimization sustainable. A short computing time is required since the design is evaluated frequently due to control engineering considerations. The closed-loop performance must be analyzed for the entire operating range using different excitation signals. Regarding directional control valves, a system model with lumped parameters is available which enables controller design simulations [4]. Furthermore, a model for system optimization must exhibit a high level of detail and a strong physical interpretability. To develop a model for control applications several model simplifications are carried out. Thus, a model with lumped parameters has a limited level of detail. Usually, the number of physical parameters is low, and the dependencies between different parameters are missing. Nevertheless, to facilitate a system optimization using a model with lumped parameters a suitable parameterization is required. The results of more detailed numerical simulations, like FEM and CFD, are used to parameterize models with lumped parameters. For the valve model in [4], a fully automated parameterization process based on preceding FEM simulations of the electromagnetic actuator is presented in [5]. In this way, the design of the valve dimensions like hardware element widths, lengths and distances can be included into an optimization vector.

Let's assume a suitable simulation setup for the model-based system optimization of a mechatronic system is avail-

[1]The authors are with the Institute of Control Theory and Systems Engineering, TU Dortmund University, D-44227, Germany, artemi.makarow@tu-dortmund.de

[2]The authors are with the Bosch Rexroth AG, D-97816 Lohr am Main, Germany, www.boschrexroth.com

able. The question is, how to perform a controller design within a fully automated multi-objective system optimization process. A trivial approach is to include the controller parameters into the overall optimization vector. In the case of the complex native controller of a directional control valve, the optimization vector would have at least 24 further entries [3]. Even if the optimizer could handle the high number of parameters and could reach convergence, it would take too much time. The challenges of a high-dimensional evolutionary optimization are, for instance, discussed in [6]. Another simple approach could be to keep the controller parameters constant while optimizing the design. In this case, the robustness of the used controller would be evaluated and not the overall system performance. Whenever the optimization algorithm provides new design parameter values, the behavior of the plant might change. Thus, a recurring controller design is essential.

The idea of this contribution is to replace the complex native valve controller with a model predictive control (MPC) concept during the offline system optimization. The intention is to reduce the number of classic controller parameters significantly while reaching a closed-loop performance comparable to the performance of the complex nonlinear PID controller. Since MPC uses a dynamic model of the plant to predict the future system evolution while minimizing a pre-defined smooth objective function, the idea is to use the whole valve model with lumped parameters as the prediction model. Hence, whenever the optimizer provides new optimization parameter values the prediction model is updated inherently. This setup with zero model mismatch leads to a design adaptive MPC using the update of the prediction model. Only three further classic controller parameters are required (refer to section III) and can be included into the optimization vector without having a great impact on the optimization procedure. All states of the model can be initialized properly since they are all available within a simulation. Classic MPC solves an optimal control problem for a moving finite horizon in every sampling interval [7], [8]. This leads to a higher closed-loop performance compared to a PID controller. However, it is assumed that the design to be improved depends on the closed-loop control performance during the system optimization. Since a proportional directional control valve is a very fast-acting nonlinear mechatronic system, a gradient-based online optimization and thus classic MPC is not real-time capable. Therefore, a developed real valve prototype could not be evaluated with the same MPC controller and thus would not constitute a performance improvement. In [9] the real-time capable but sub-optimal model predictive trajectory set control (MPTSC) is introduced and applied to a real proportional directional control valve. Hereby, a simplified linear prediction model is used. MPTSC approximates classic MPC with a control horizon of $n_\mathrm{c} = 1$ and addresses industrial applications. A gradient-based online optimization is not required. The performance is similar to the nonlinear PID controller while the number of free parameters is low. Thus, after finishing the simulation-based development, the prototype can either be evaluated with MPTSC using a simplified prediction model or the nonlinear PID controller.

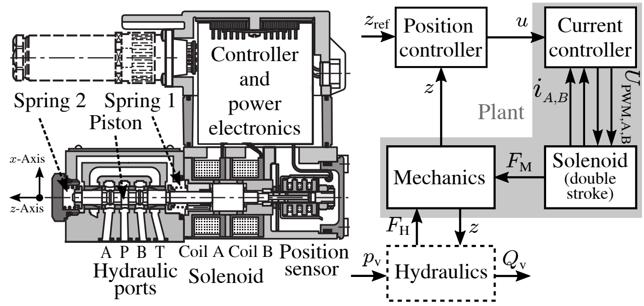

Fig. 1: Cross section of the proportional directional control valve 4WRREH6 [10]. The block diagram illustrates the mechatronic character of the valve and the cascaded control concept. The gray highlighted area on the right is the plant.

Section II provides a general overview about the developed holistic system optimization of a proportional valve. It aims to clarify at what point of the system optimization process the closed-loop is important. Section III explains MPTSC and the required configuration. In section IV the contribution is evaluated. Finally, section V summarizes the results and provides an outlook on further work.

II. HOLISTIC VALVE SYSTEM OPTIMIZATION

Proportional Directional Control Valve

In this contribution, the proportional valve 4WRREH6 [10] is investigated. Figure 1 shows the cross section and the block diagram of the valve. The task of a proportional directional control valve is to route oil from the pressure port P to the working ports A or B. The piston position adjusts the oil flow $Q(z(t), p_\mathrm{v}(t))$ as a function of the stroke $z(t)$ and the supply pressure $p_\mathrm{v}(t)$ at port P. Hence, the fast and precise one-dimensional stroke or position control is of central interest. The 4WRREH6 valve has a double stroke solenoid. Two coils work in contrary motion directions to achieve high dynamics. Two pre-loaded springs ensure the force-type connection of the movable parts. A sensor signal of $z(t) = \pm 100\,\%$ provides information about a fully opened working port A or B. The interactions between the subsystems of different domains are controlled with a cascaded control concept and power electronics. In this contribution, the current controller and the power electronics are part of the plant and the valve model. Their operation functions are known exactly. The native nonlinear PID position controller is replaced with MPTSC. The solenoid model has a current and a force model. Both sub-models are based on the Hammerstein model structure. Thus, dynamic effects like eddy currents within the electromagnetic actuator are modeled with linear dynamics. For instance, the characteristic force curves represent a static nonlinear relationship between the electrical currents in coil A and B, $i_\mathrm{A}(t)$ and $i_\mathrm{B}(t)$, the stroke $z(t)$ and the actuator force $F(t)$. During real operation, a sudden change in a current signal leads to dynamic effects. The force value $F_\mathrm{stat}(t)$ pre-determined by the static curves can only be reached after a certain delay. The linear dynamics are used to model this dynamic effects. Linear dynamics require less identification data than nonlinear approaches. Thus, the simulation time of the computationally expensive FEM can be reduced. The mechanics model is a second order differential equation, the mass-spring-damper system with a nonlinear friction term. Hydraulic effects are omitted since the working ports are mechanically locked during the controller design. More detailed information about the model with lumped parameters can be found in [4] and [5]. Figure 2 presents only a small part of the whole valve model within the developed parameterization procedure. Since the modeling of the electro-magnetic actuator is the main challenge, the Hammerstein model structure is illustrated.

Optimization and Parametrization Process

Since the level of detail of the model with lumped parameters is not high enough to perform a model-based system optimization, a 2D FEM model of the electromagnetic actuator is utilized. The idea is to use a more complex simulation tool to parameterize the valve model for control applications. The parameterization of a simplified model based on more detailed numerical methods is known in the literature. However, either only static curves are used within the model with lumped parameters [11], or reluctance networks are applied like in [12] and [13]. When using static curves only, the model accuracy is not sufficiently high enough for fast-switching valves. The reluctance networks model assumptions are not always valid for varying designs of the actuator and thus require some human expertise. The use of reluctance networks within a fully automated optimization process is limited. The mass-spring-damper approach with nonlinear friction provides a sufficiently high level of detail for the mechanics sub-model. Figure 2 presents the developed holistic system optimization process for a proportional valve. It aims to exploit the hidden potential of the current valve design. Thus the current valve serves as the reference. Since the closed-loop performance is evaluated based on different criteria, like rise time, settling time and overshoot characteristic, a global optimization algorithm is chosen. A modified version of the optimization algorithm NSGA-II [14] facilitates the evolution of the system optimization vector values using recombination and mutation operators on the best previous parameters. The design parameters which are essential for the system optimization can be derived from a preceding sensitivity analysis. However, this optimization vector constitutes a pre-defined parameter set including geometric design parameters like coil dimensions, physical parameters like spring constants and controller parameters. Whenever geometric design parameters change, the static and dynamic behavior of the solenoid changes, too. A static FEM simulation provides the updated characteristic curves, and a short transient FEM simulation provides the required synthetic data to identify the linear dynamics. Moreover, some further parameters like ohmic resistors within the valve model are affected by the design change. A conversion block transforms geometric data into these physical parameters. This parametrization and optimization approach is fully

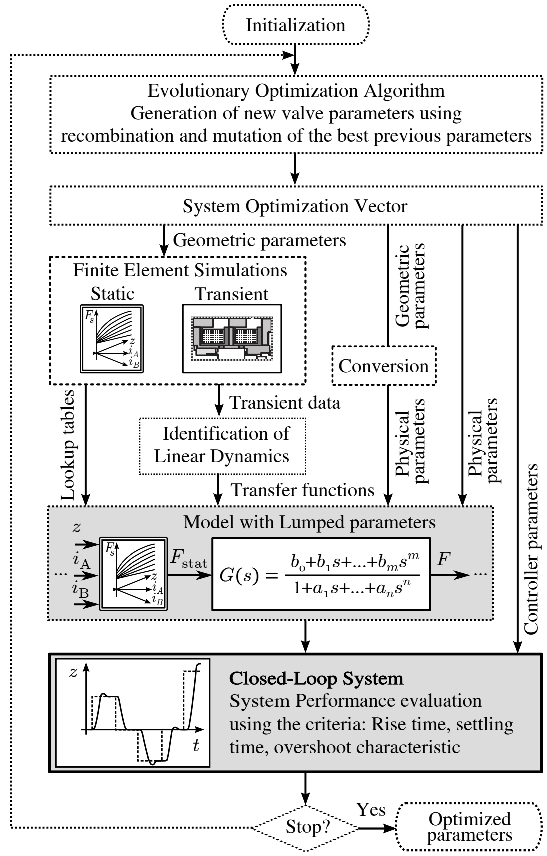

Fig. 2: The valve model with lumped parameters exhibits a Hammerstein model structure and is parameterized with FEM simulation results. After parameterizing the valve model, the closed-loop system is of central interest.

automated and is presented in [5] in more detail. A standard desktop PC requires approximately one hour for a single parameterization loop starting from a given optimization vector and ending with objective function values. However, this holistic parameterization process takes less time than simulating the closed-loop based exclusively on transient FEM models for different reference signals. This other kind of approach is called co-simulation and is, for instance, used in [15]. The contribution of this paper is the closed-loop system in Figure 2. Two approaches exist to deal with the controller design during system optimization:

a) Including controller parameters into the system optimization vector:
   - Design invariant variations of optimization vector values enforce time-consuming FEM simulations
   - Convergence in an acceptable time is not expectable for a high number of optimization parameters
   + Integration of controller design requires no extra programming effort
b) Subordinated multi-objective controller design:
   - Selection of a solution or individual from a multi-dimensional Pareto front is difficult to automate
   + Reducing significantly FEM simulation time

The advantages (+) and disadvantages (-) highlight that approach a) is particularly suitable with a model predictive control concept. After parameterizing the valve model, the nonlinear differential equations can be used as the exact prediction model of the plant of MPC. Since the number of classic controller parameters decreases significantly due to the inherent model update, the system optimization procedure focuses mainly on the improvement of the hardware design. Approach b) is solved by applying a cascaded optimization strategy in [16]. This idea is similar to [6].

III. OUTER POSITION CONTROLLER

The valve model introduced in section II constitutes a single-input system. The nonlinear state equations $\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), u(t))$ with q states are solved using finite-differences with the forward Euler method and a dedicated step size Δt_s:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{f}(\mathbf{x}_k, u_k)\, \Delta t_\mathrm{s}, \quad \mathbf{x}_{k=0} = \mathbf{x}_0. \tag{1}$$

The vector $\mathbf{x}_k \in \mathbb{R}^q$ represents the state vector with $\mathbf{x}(t) = [x_1(t) = z(t), x_2(t), ..., x_q(t)]^\intercal$ at the discrete time instance k and $u_k \in \mathbb{R}$ the corresponding control input. The output of the position controller is limited to:

$$u_\mathrm{min} \leq u_k \leq u_\mathrm{max}. \tag{2}$$

Native Valve Position Controller

Figure 3 presents the basic block diagram of the native valve controller. This position controller is a combination of an augmented PI-controller with an additional state feedback controller. Piecewise linear curves define the proportional and integral amplifications. Thus, different operating ranges like the small and large signal performances can be handled with a single controller. The amplification of the PI-controller depends on the error $e(t)$. The state feedback controller $D(z)$ calculates the time derivatives of the stroke $z(t)$ and is applied to avoid overshooting. A PID controller is just able to adhere to state and input constraints implicitly by adjusting the parameter value ranges. However, the output is subject to a simple limiter. For this reason, an anti-windup function is implemented to avoid integrator windup. The parameters k_d and k_aw are free to optimize. In total, the controller exhibits 24 free parameters. The controller design is based on an evolutionary multi-objective optimization and is presented in [3]. Although this complex controller requires a time-consuming controller design, it is real-time capable on low-cost processing units. Moreover, the stroke $z(t)$ is the only system state needed to perform the closed loop. Hence, the commanded reference stroke signal $z_\mathrm{ref}(t)$ is a scalar.

Model Predictive Trajectory Set Control

Solving an optimal control problem within a sampling interval leads to the optimal control input u_k^*. The implicit control law at every time step k is then defined as $u_k = u_k^*$. Regarding classic MPC, u_k is chosen from a continuous value range $u_k \in \mathbb{R}$. MPTSC discretises the input domain, the input u_k is thus chosen from a discrete value range $u_k \in \mathbb{A}_k$ with $\mathbb{A}_k \subset \mathbb{R}$. The (sub-)optimal control input u_k^* results from:

$$u_k^* = \arg \min_{u \in \mathbb{A}_k} J(\mathbf{x}_k, u) \tag{3}$$

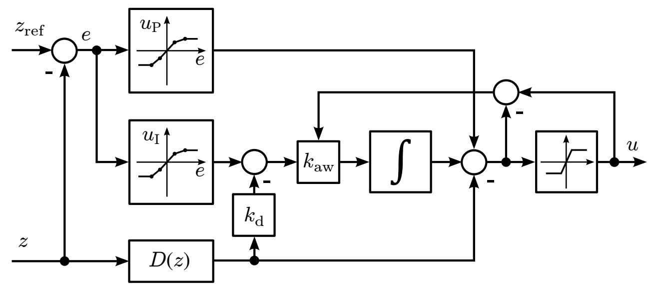

Fig. 3: Basic structure of the native valve controller with 24 parameters including an anti-windup.

subject to (1), (2) and the state box constraints

$$\mathbf{x}_\mathrm{min} \leq \mathbf{x}_k \leq \mathbf{x}_\mathrm{max}. \tag{4}$$

The basic formulation of MPTSC uses a control horizon of $n_\mathrm{c} = 1$. Hence, every possible input candidate is kept constant on the prediction horizon horizon t_p. In this manner, a set of state trajectories is predicted and evaluated by means of the objective function $J(\cdot)$ in every sampling interval Δt_s. The input candidate which leads to the least objective function value is chosen and applied to the plant. The optimal control problem in (3) is solved by applying the minimum operator. Gradient-based online optimization is not necessary and enables the implementation of non-smooth user-defined objective functions. The subset $\mathbb{A}_k$ provides different input candidates at every time instance k to enable a quasi-continuous input value range. First, the input domain is discretized in an equidistant and sparse manner:

$$u_\mathrm{lin} \in \mathbb{D} := \{u_\mathrm{min}, u_\mathrm{min} + \Delta u, u_\mathrm{min} + 2\,\Delta u, ..., u_\mathrm{max}\}. \tag{5}$$

Hence, the number of available input candidates is defined by the equidistant discretization and the step size Δu. Two polynomial functions of order r are designed to map the input candidates resulting from the linear discretization $u_\mathrm{lin} \in \mathbb{D}$ to candidates of an adaptive input value set $u \in \mathbb{A}_k$ with $g(u_\mathrm{lin}) : \mathbb{D} \to \mathbb{A}_k$:

$$g(u_\mathrm{lin}) = u = \begin{cases} p_1\, u_\mathrm{lin}^r + p_2\, u_\mathrm{lin} + p_3, & \text{if } u_\mathrm{lin} \geq 0 \\ p_4\, u_\mathrm{lin}^r + p_2\, u_\mathrm{lin} + p_3, & \text{if } u_\mathrm{lin} < 0. \end{cases} \tag{6}$$

The polynomial coefficients p_1, p_2, p_3, p_4 are recalculated in every sampling interval considering the conditions:

$$\begin{gathered} g(u_\mathrm{max}) = u_\mathrm{max},\, g(u_\mathrm{min}) = u_\mathrm{min}, \\ g(0) = u_{k-1},\, g'(0) = 0. \end{gathered} \tag{7}$$

This mapping allows a finer discretization around the last input value u_{k-1}. The performance difference between classic MPC with $n_\mathrm{c} = 1$ and MPTSC with an adaptive input domain discretization is negligible [17]. However, in contrast to MPC, MPTSC is real-time capable even for a sampling frequency up to the kilohertz range [9]. Theoretical stability analysis is not part of this contribution. If the discretization step size Δu is chosen sufficiently small, the stability approaches of classic MPC with $n_\mathrm{c} = 1$ can be applied [8]. This assumption is valid especially in the case of stable open-loop dynamics. The following quadratic objective function evaluates the open-loop performance in every sampling interval:

$$J(\mathbf{x}_k, u) \approx \Delta t_{\mathrm{s}} \sum_{l=1}^{l=n_{\mathrm{p}}} \left((\hat{\mathbf{x}}_{k,l} - \mathbf{x}_{\mathrm{f},k})^{\intercal} \mathbf{Q} \, (\hat{\mathbf{x}}_{k,l} - \mathbf{x}_{\mathrm{f},k}) \right). \quad (8)$$

During the prediction, indicated by the variable l with $\hat{\mathbf{x}}_{k,l}(u) := \hat{\mathbf{x}}_l(\mathbf{x}_k, u)$, the same sampling step size Δt_{s} is applied until the discrete prediction horizon n_{p} is reached. $\mathbf{Q}$ is chosen to be a diagonal matrix with only $q_1 = 1$ and $q_2 \neq 0$. The vector $\mathbf{x}_{\mathrm{f}}(t) = [z_{\mathrm{ref}}(t), x_{2,\mathrm{ref}}(t) = 0, ..., x_{q,\mathrm{ref}}(t) = 0]$ denotes the state references of the state space control concept. The reference for the position $z_{\mathrm{ref}}(t)$ is a function of time to provide reference position signals compared to the native PID controller. Since the future course of the reference state vector $\mathbf{x}_{\mathrm{f}}(t)$ is unknown during real valve operation, the sampled reference state vector $\mathbf{x}_{\mathrm{f},k}$ is kept constant over the prediction horizon n_{p}. Regarding the closed-loop control, the task is the transition between the initial states $\mathbf{x}_0$ and the final states $\mathbf{x}_{\mathrm{f}}(t)$. The weights q_1 and q_2 penalize the position and velocity errors with $\dot{z}(t) = x_2(t)$. Tuning the weights is very intuitive. Increasing the weight q_2 leads to a more damped closed-loop performance with less overshooting. However, the behavior occurs during the large range operation as well as during the small range operation. Regarding the real valve's small range operation, more importance is attached to fast dynamics than preventing overshooting. Hence, an additional degree of freedom is required. Although MPTSC exhibits a control horizon of $n_{\mathrm{c}} = 1$, it explicitly adheres to input and state constraints defined in (2) and (4). The idea is to insert a box state-constraint for the velocity state $x_{2,\mathrm{lim}}$. In this way, the weight q_2 can be decreased to reach higher dynamics for the small range performance. Regarding the large range operation, the limited velocity prevents the stroke from overshooting. More details are discussed in section IV. Since a control horizon of $n_{\mathrm{c}} = 1$ is utilized, the prediction horizon n_{p} becomes an optimization parameter too. In total, three controller parameters are necessary and subject to the system optimization.

IV. Analysis and Experiments

Original Valve Design

For the first analysis, the original design and physical parameters are utilized. After parameterizing the valve model with the presented process in Figure 2, the controller design for the native valve controller and MPTSC is carried out. A step-shaped position reference signal which covers the whole operating range is commanded to both controllers. During the multi-objective evolutionary optimization of the native controller, different step amplitudes are evaluated. An elite individual is chosen from the multi-dimensional Pareto front. Figure 4 presents the results. The variable T is a constant. Since the MPTSC has only three adjustable parameters, the controller design is carried out manually. First of all, the prediction horizon must be chosen which enables a stable closed-loop performance. Afterwards, the parameters q_2 and $x_{2,\mathrm{lim}}$ are tuned to find a compromise between the

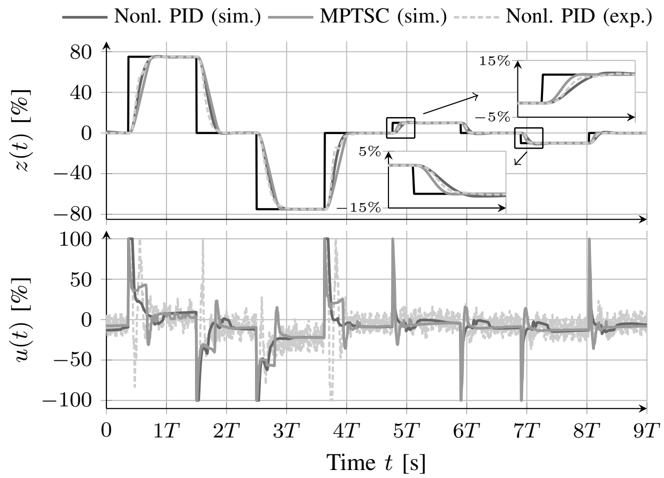

Fig. 4: Closed-loop performances of the native valve controller and MPTSC using the model which is parameterized with original valve design parameters. The experimental valve operation validates the high simulation quality of the valve model.

rise time and the overshoot. As desired, both closed-loop performances are nearly identical even though the number of parameters differs strongly. MPTSC does not outperform the native PID significantly due to the limited control horizon $n_{\mathrm{c}} = 1$. This desired property leads to a prototype which is suitable to be controlled with the guaranteed real-time capable native nonlinear PID controller. The constant increase of the stroke $z(t)$ indicates the explicit adherence to the box constraint $x_{2,\mathrm{lim}}$ of MPTSC. To evaluate the model quality, the controller parameters resulting from the model-based controller design are applied directly to the real valve controller unit. The performance of the valve of a real experiment is also presented in Figure 4. This parameter set is able to realize a stable control with a few minor differences compared to the simulation. The model error, the limited robustness of the complex native PID controller and the real sensor noise lead to the differences during experimental operation. The detailed valve model used for system optimization is not real-time capable. Therefore only simulation-based results are presented for MPTSC. For the remainder, the native PID simulation-based closed-loop performance for the original valve design is treated as the reference. The rise times, the settling times and the overshoot characteristics are evaluated with just three additive objective functions:

$$T_{\mathrm{r},\Sigma} = \sum_{i=1}^{v} \frac{T_{\mathrm{r},i}}{T_{\mathrm{r,ref},i}}, \; T_{\mathrm{s},\Sigma} = \sum_{i=1}^{v} \frac{T_{\mathrm{s},i}}{T_{\mathrm{s,ref},i}}, \; Mo_{\Sigma} = \sum_{i=1}^{v} Mo_i.$$

The variable v denotes the number of evaluated steps. The rise times $T_{\mathrm{r,i}}$ and the settling times $T_{\mathrm{s,i}}$ are normalized to the references $T_{\mathrm{r,ref},i}$ and $T_{\mathrm{s,ref},i}$. The overshoot amplitudes Mo_i are not normalized to avoid dividing by zero. In Figure 4 the simulation based PID provides the reference objective values $T_{\mathrm{r},\Sigma} = 100\,\%$, $T_{\mathrm{s},\Sigma} = 100\,\%$ and $Mo_{\Sigma} = 3.8\,\%$ concerning the shown step-shaped stroke reference signal. MPTSC reaches slightly better but comparable objective values $T_{\mathrm{r},\Sigma} = 89\,\%$, $T_{\mathrm{s},\Sigma} = 74.6\,\%$ and $Mo_{\Sigma} = 1.2\,\%$.

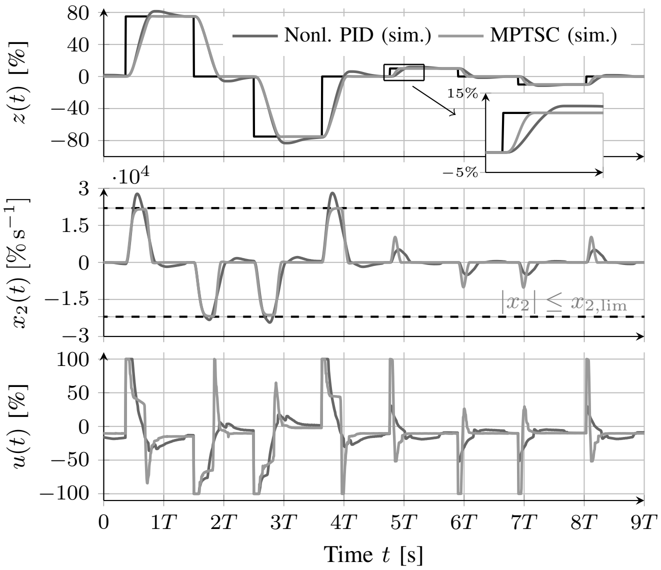

Fig. 5: Closed-loop performance for the case when the design is modified and the controller parameters are kept constant.

Modified Valve Design

The modification of the valve presented in this contribution does not provide necessarily an improvement of the system performance. It is merely intended to show a possible evolution of the optimization vector values during the system optimization. The design parameters of the actuator are adjusted to reach higher dynamics theoretically. Hence, for instance, the number of coil turns is increased to reach a higher magnetic flux linkage within the solenoid. The parameterization process in Figure 2 is applied again. Figure 5 illustrates the case when the controller parameters of both control concepts are kept constant. Since the native nonlinear PID controller has no system knowledge, a design adaptive character is missing. The objective values deteriorate significantly to $T_{\mathrm{r},\Sigma} = 121.4\,\%$, $T_{\mathrm{s},\Sigma} = 225\,\%$ and $Mo_{\Sigma} = 32.7\,\%$. MPTSC is able to nearly reach the closed-loop performance of Figure 4 due to its inherent model update. It reaches the objective values $T_{\mathrm{r},\Sigma} = 98.9\,\%$, $T_{\mathrm{s},\Sigma} = 81.7\,\%$ and $Mo_{\Sigma} = 1\,\%$. This fact saves overall system optimization time and enables an efficient fully-automated design optimization. Thus, the system optimization focuses mainly on the design improvement. If a new controller design is carried out for the modified valve design, the native PID controller can meet the requirements again. The three parameters of MPTSC can also be adjusted to increase the control performance. However, these three MPTSC parameters are adjusted by the system optimization algorithm without a great overhead. In contrast, the parameters of the PID controller cannot be included into the system optimization vector. Due to the high complexity, the convergence of the system optimization is not guaranteed in an acceptable time. In the case of a high number of optimization parameters, approach b) and hence a cascaded optimization procedure is required [16]. Hereby, all optimization parameters which do not have an impact on the time-consuming FEM are subject to a faster subordinated optimization loop.

V. Conclusions and Future Work

This contribution introduces MPC in the context of the model-based system optimization of a hydraulic valve. The system performance is evaluated by simulating the closed-loop control. When using the valve model as the plant and the prediction model, the effort for the controller design decreases significantly. The suboptimal MPTSC is chosen to develop a prototype which is real-time capable concerning experimental operation. This approach addresses fully-automated system optimization procedures for industrial applications. Further work is concerned with the evaluation of the system optimization results in more detail.

References

[1] K. Thramboulidis, "Challenges in the development of mechatronic systems: The mechatronic component," in *International Conference on Emerging Technologies and Factory Automation (EFTA)*, 2008.

[2] J. van Amerongen, "Mechatronic design," *Mechatronics*, vol. 13, no. 10, pp. 1045–1066, 2003.

[3] J. Krettek, D. Schauten, F. Hoffmann, and T. Bertram, "Evolutionary hardware-in-the-loop optimization of a controller for cascaded hydraulic valves," in *International Conference on Advanced Intelligent Mechatronics (AIM)*, 2007.

[4] A. Makarow, J. Braun, C. Krimpmann, T. Bertram, G. Schoppel, and I. Glowatzky, "System model of a directional control valve for control applications," in *The Fourteenth Scandinavian International Conference on Fluid Power (SICFP)*, 2015.

[5] A. Makarow, J. Braun, M. Keller, T. Bertram, G. Schoppel, and I. Glowatky, "Holisitc approach to the system optimization of a proportional valve," in *International Fluid Power Conference (IFK)*, 2018.

[6] T. Friedrich and S. Menzel, "A cascaded evolutionary multi-objective optimization for solving the unbiased universal electric motor family problem," in *IEEE Congress on Evolutionary Computation*, 2014.

[7] M. Morari and J. H. Lee, "Model predictive control: past, present and future," *Computers & Chemical Engineering*, vol. 23, no. 4-5, pp. 667–682, 1999.

[8] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. Scokaert, "Constrained model predictive control: Stability and optimality," *Automatica*, vol. 36, no. 6, pp. 789–814, 2000.

[9] A. Makarow, M. Keller, C. Rösmann, T. Bertram, G. Schoppel, and I. Glowatzky, "Model predictive trajectory set control for a proportional directional control valve," in *IEEE Conference on Control Technology and Applications (CCTA)*, 2017.

[10] Bosch Rexroth AG, "Type 4WRREH6; 4/3 directional control valve, directly controlled, with electrical position feedback and integrated electronics (obe)," in *Datasheet, Version RE 29041/03.10*.

[11] M. Erhard, G. Schoppel, and J. Weber, "Simulation-based design of a direct-operated proportional pressure relief valve," in *International Fluid Power Conference (IFK)*, 2012.

[12] D. Wehner, S. Helduserand, J. Weber, and G. Schoppel, "Reluctance network for simulation of proportional solenoids in fluid power valve systems," in *Fluid Power and Motion Conference*, 2010.

[13] M. Fiedler, S. Helduser, and D. Wehner, "Coupled simulation for the virtual product development of electro-hydraulic valves," in *International Fluid Power Conference (IFK)*, 2010.

[14] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.

[15] S. Kanerva, J. Kaukonen, A. Szucs, and T. Hautamaki, "Coupled FEM-control simulation in the analysis of electrical machines and converters," in *IEEE International Power Electronics and Motion Control Conference (IPEMC)*, 2006.

[16] A. Makarow, J. Braun, C. Rösmann, G. Schoppel, and T. Bertram, "Cascaded evolutionary multi-objective system optimization for a proportional directional control valve," in *IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, 2018, (accepted).

[17] A. Makarow, M. Keller, C. Rösmann, and T. Bertram, "Model predictive trajectory set control with adaptive input domain discretization," in *American Control Conference (ACC)*, 2018, (accepted).