Identification of Critical Operating Conditions for Robust Evolutionary Optimization of Hydraulic Valve Controllers

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Abstract

The design and optimization of complex technical systems is an important task in engineering and development. Evolutionary hardware-in-the-loop (HIL) optimization constitutes a powerful method as it performs robust search in complex and high dimensional search spaces. The operating conditions severly influence the quality and performance that a solution subject to an HIL evaluation is able to achieve. Thus it is essential to properly control and select these operating conditions in the context of HIL optimization in order to accomplish robust valve performance across a large range of processes and applications. The identification of crucial operating conditions in terms of stimuli, disturbances and external parameters such as hydraulic load and pressure constitutes an optimization task by itself. The approach presented in this paper employs evolutionary optimization to identify test scenarios at the boundaries of the operating envelope under which regulation of the valve position is particular difficult. The parametrization and optimization of these conditions are illustrated and experimental results under realistic valve operation conditions are provided.

KEYWORDS: valve control, evolutionary optimization, operating conditions

1. Introduction

Modern methods of "Computational Intelligence" (CI) provide powerful tools for the design, development and optimization of technical systems. The combination of computer-based optimization methods with HIL-experiments on prototypes accelerates the design process as it systematically selects the most promising solutions and such reduces the number of designs to be manufactured and tested in the course of development. Evolutionary algorithms (EA) inspired by the natural evolution improve a population of candidate solutions iteratively over several generations. This property enables the heuristic algorithm, to approximate the globally optimal solution even in highly non-linear or complex solution spaces. In addition to their robust search EAs allow for optimization with respect to multiple conflicting objectives. Almost all technical design problems are inherently multi-objective, which provides EAs with a distinct advantage over numerical, nonlinear scalar optimization methods. In the context of controller optimization for hydraulic valves evolutionary HIL-optimization has proven successful on multiple occasions in the past /1/, /2/ and /3/. The primary goal is the optimization of a highly parameterized non-linear controller for a directional control valve. A digital nonlinear gain PID-controller controls the position of the valves piston measured by an inductive sensor. A fitness evaluation of candidate parameters is based on the aggregation of characteristic features such as rise time (Tr), maximal overshoot (MO) and integral of square weighted error (ISTE) of the closed loop response with respect to a reference stimulus composed of multiple steps in the small, medium and large signal range. This forms the experimental scenario used for the optimization of operating conditions in **Section 4.** Another scenario, involving a controlled pressure relieve valve is presented in **Section 3.**

Optimization of control parameters, regardless of the method, requires the definition of operating conditions under which the controller is tested and its performance is evaluated according to the above mentioned criteria. In the context of HIL controller optimization, the ambient conditions, such as pressure, load and disturbances constitute the key aspects of valve operation. The proper choice of operating conditions significantly affects the robustness of the optimized control system. However, in the context of optimization of hydraulic valve controllers, the identification of crucial operating conditions might be as complex as the actual optimization of the controller itself. At first a suitable reference stimulus is required to assess the closed loop response. In addition the ability of the controller to reject disturbances is equally important for its robust operation. As it is impossible to evaluate the controller under a large spectrum of disturbances it is important to identify the most critical and representative disturbances beforehand prior to controller optimization. The basic idea of the presented approach is to apply evolutionary algorithms to identify critical operating conditions and scenarios.

In contrast to common co-evolutionary algorithms, in which operating conditions and controllers co-evolve according to the predator-prey principle /4/, our approach separates both tasks of finding optimized controllers for the most critical operating conditions. This separation is valid as if one assumes that difficult operating conditions affect the performance of optimal or near optimal controllers in a similar manner. Thus it is possible to identify a set of critical operating conditions and then apply these static conditions for the fitness evaluation in the subsequent controller optimization. It is then possible to iterate this process by refining operating conditions on the basis of the currently best controller. **Figure 1** illustrates schematically the interaction of the various aspects of the method. The controller that performs optimal under the initial operating conditions provides the benchmark to identify more challenging operating conditions in return. This cycle of intertwined controller optimization and operating condition refinement is repeated until convergence.

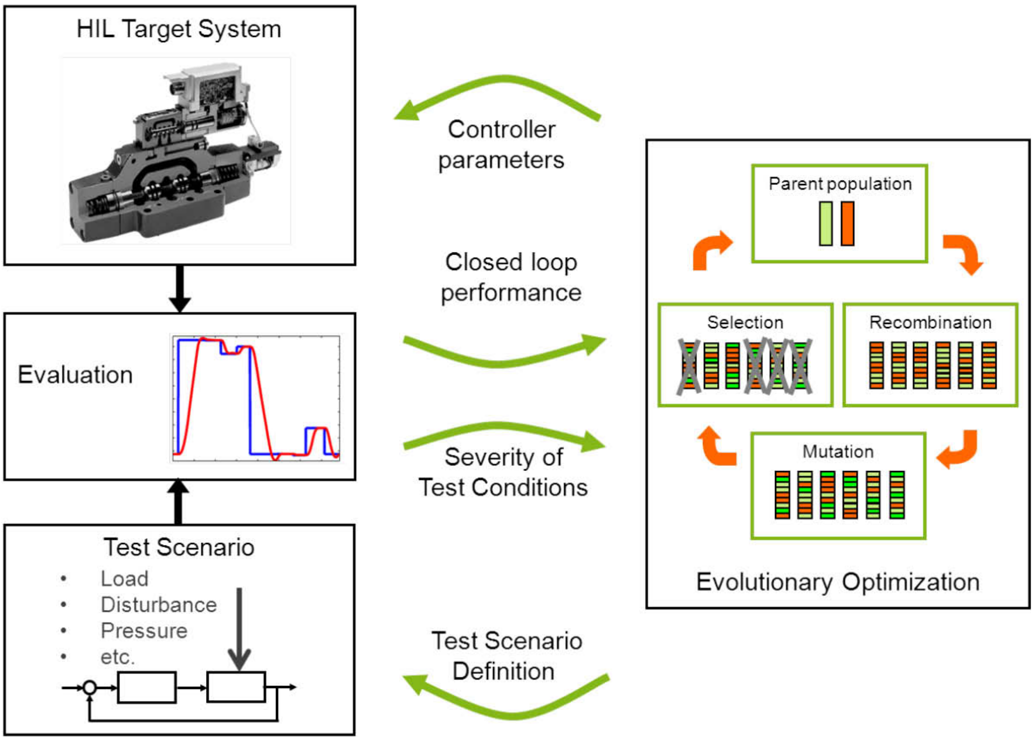

Figure 1: HIL optimization scheme

1.1. Evolutionary optimization

Evolutionary algorithms in contrast to numerical optimization methods operate with a population of candidates rather than iterating a single solution. These individuals evolve across several generations during which they are subject to competition, selection and variation by means of genetic operators such as mutation and recombination inspired by natural evolution. Solutions that are superior within their generation with respect to the objectives are selected as parents and reproduce the offspring of the next generation. Similar to the natural evolution, this algorithm constitutes a robust and powerful method to find optimal solutions for complex problems. For details on EAs the interested reader is referred to /5/.

Most realistic optimization problems hardly focus on a single objective, but rather consider multiple potentially conflicting objectives. The a priori aggregation of objectives into a single criterion is difficult to accomplish as criteria from different domains are usually defined with different metrics and scales. To avoid such an a priori aggregation, multi-objective evolutionary algorithms (MOEA) generate a set of optimal compromise solutions that approximates the so called non-dominated or Pareto optimal solutions. From this approximate Pareto set the expert selects his final solution according to his subjective preferences among the objectives. The MOEA employed in this paper is the popular NSGA-II by Deb et al. /6/. A general overview on MOAEs is provided in /7/. For multi-objective optimization the conventional fitness based ranking becomes obsolete and selection relies on the concept of dominance. A solution dominates another solution if it is superior in at least one objective and not inferior in any other objective. In this case improvement of a Pareto optimal solution in one objective comes at the cost of degradation in at least one other conflicting objective.

2. Parameterization of operating conditions

First of all, the optimization of operating conditions requires their proper parameterization. In an HIL optimization only operating conditions that can be modified automatically can be taken into account. In both experimental setups described in this article an additional load valve is used to influence the closed loop performance of the controlled main valve. In the first experiment (see **Section 3**) a flow control valve dynamically changes the oil flow the controlled pressure relive valve has to compensate. The second experimental setup uses a directional control valve to simulate a dynamic load that influences the controller performance of the main valve. **Section 4.1** explains this test bed in detail.

The periodic reference signal for both valves is generated by the real-time control system. The investigation considers three types of signals with different shape, namely a sinusoidal signal, a rectangular signal and a signal composed of multiple harmonics in terms of a Fourier series with the ability to approximate general wave forms.

The single frequency sinusoidal and rectangular signals are defined in terms of the minimal and maximal amplitude and frequency f of the secondary valves set value function as shown in **Figure 2**. A preliminary investigation revealed that this particular parameterization better decouples their impact on the disturbance in contrast to a definition in terms of offset and amplitude. The $\Delta\varphi$ defines relative phase of the periodic signal at the start of the experiment. In case of the tracking problem in **Section 4.3** the parameter $\Delta\varphi$ describes relative phase between the primary reference stimulus and the disturbance, which has a substantial impact on the emergence of interference between reference and disturbance. The length of the high and low pulse of the rectangular signal are not identical but are determined by the additional parameter (w) that defines the pulse-width as the ratio between t_1 and t_2.

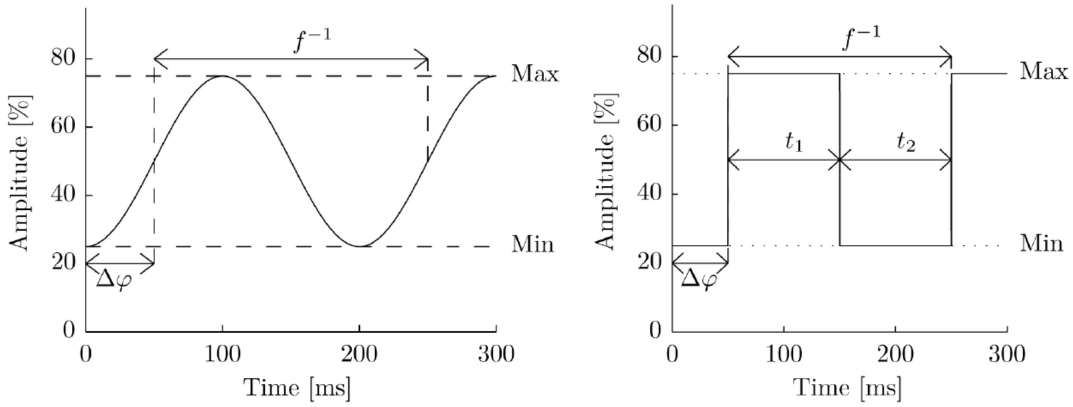

Figure 2: Parameterization of signals

The Fourier series is limited to the superposition of the first k=4 harmonics: $F(x) = \sum_{n=1}^{k} a_n \cos\big(n(2\pi f x + \Delta\varphi)\big) + b_n \sin(n(2\pi f x + \Delta\varphi))$.

The coefficients a_n and b_n are optimized and the resulting signal is normalized such that the overall amplitude is bounded by the limits *Min* and *Max*. This representation results in 2k additional parameters subject to optimization.

Conditions that allow for automatically modifications but cannot be chanced fast enough to generate dynamic disturbances can be considered as a single real-valued parameter. These conditions are adapted in between each HIL experiment but remain constant during the evaluation. In all experiments in **Section 4** the pressure of the system is an example of an operating condition described by a scalar optimization parameter. Other disturbances and operating conditions such as temperature are more difficult to vary and control at a rate that is sufficient for fitness evaluation. They are therefore not considered but rather kept constant during the experimentation.

3. Optimization of operating conditions for pressure relieve valves

The general task of a pressure relieve valve is to limit the system pressure at a constant level. This constitutes a regulation problem for the controller which is supposed to reject disturbances. The primary objective of the optimizing operating conditions is to verify a sufficient degree of robustness of the closed loop behavior. For that purpose the optimization identifies the most difficult conditions for which the performance of the reference controller degrades most. During the identification of the operating conditions the parameters of the controller remain fixed, thus the optimization seeks out the particular weaknesses of a controlled pressure relieve valve in terms of robustness as it reverses the very same set of objective functions employed in controller optimization. The resulting approximate Pareto set constitutes the operating conditions that deteriorate the closed loop performance criteria in the worst possible manner.

3.1. Experimental hardware setup

The hardware setup shown in **Figure 3** is composed of a primary flow control valve which determines the hydraulic flow to be compensated by the subsequent secondary relieve valve. The feedback controlled pressure relieve valve regulates the pressure p_a at a constant reference p_{set} which is although an optimization parameter. The reference stimulus of the flow control valve is a rectangular disturbance signal, which maximizes the integral of the squared error (ISE) and maximal deviation (MO) of p_a from the constant reference during regulation.

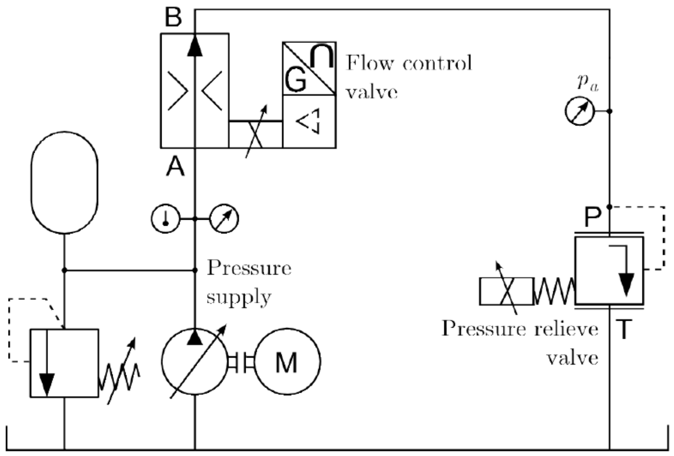

Figure 3: Experimental setup - pressure relieve valve

3.2. Results

The optimization problem has the two objectives ISE and MO and six parameters. The parameters and their ranges for reference pressure and disturbance signal are shown in **Table 1**.

Parameter:	Range:	Unit:	Parameter:	Range:	Unit:
p_{set}	[3 200]	bar	*Min*	[0.1 3.08]	l/min
f	[0.1 80]	Hz	*Max*	[0.1 3.08]	Hz
$\Delta\varphi$	[-100 100]	%	w	[0 100]	%

Table 1: Range of parameters

The evolution of both criteria over 50 generations is shown in the left part of **Figure 4**. The approximate Pareto front is spanned by the final non-dominated solutions marked by a circle and is shown in more detail in the right part of this figure.

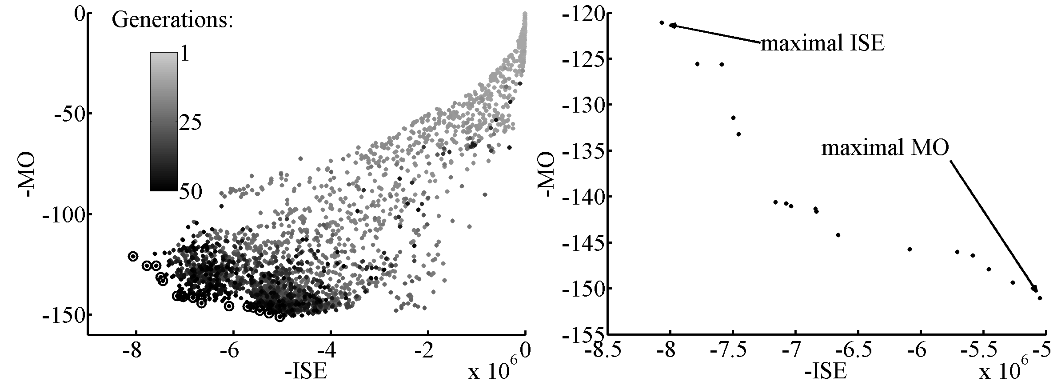

Figure 4: Optimization results; Left: development of the optimization objectives over the generations. Right: final nondominated set of solutions

The two extreme disturbances at the boundaries of the Pareto front and the corresponding response of the regulation are shown in **Figure 5**. The most harmful disturbance signal causes a significant deviation from the reference. The analysis reveals that the *Min* value of the disturbance signals converges to its lower limit, thus causing low oil flow. The PI-controller of the pressure relieve valve closes the valve completely but is unable to increase the pressure p_a quickly due to the low flow rate. At the same time the integrator block of the controller saturates the actuating signal to its upper limit. When the oil flow steps up almost to its maximum capacity a large overshoot in pressure is caused. The subsequent transition to minimal oil flow occurs at an instant that causes a significant undershoot due the integrating controller.

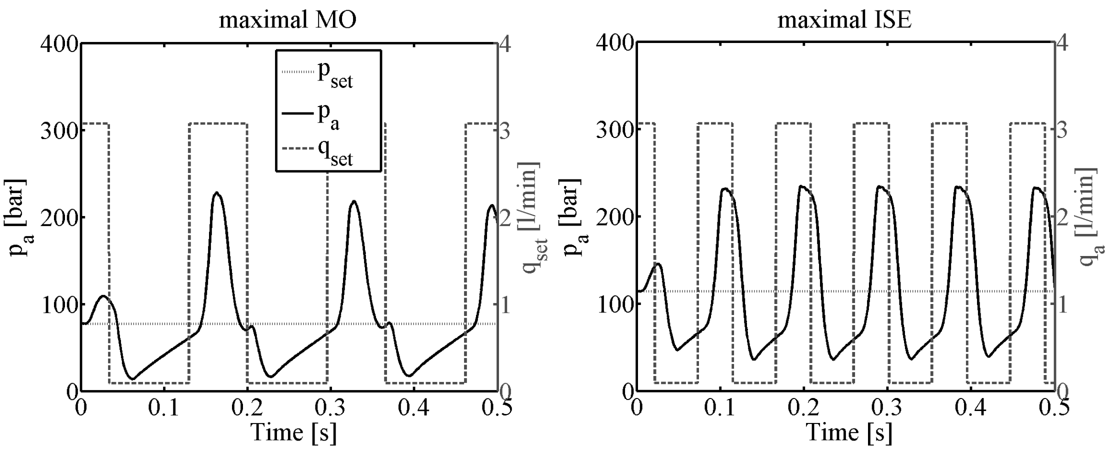

Figure 5: The pressure response p_a and the disturbance signal q_{set} for the two extreme solutions of the Pareto front.

While it is intuitive to that the worst disturbance utilizes the minimal and maximal amplitude, the identification of the most harmful frequency *f*, pulse-width *w* and set value p_{set} provides the expert with valuable insight about problematic operating conditions and worst case scenarios. This knowledge is helpful in the redesign or improvement of the original controller structure, for example consideration of a more elaborate anti-windup system.

4. Identification of critical operating conditions for proportional valves

This experiment is concerned with the optimization of a controller for an NG6 proportional valve. The controller is a PID controller with additional nonlinearities described by a total of 24 parameters. The closed loop response to a sequence of step inputs of different magnitude is evaluated in terms of five partially conflicting criteria including rise time, overshoot and integral of squared error. The operating conditions are defined in terms of the pressure and the hydraulic flow at the working ports of the valve, which constitute either at static or dynamic load disturbance.

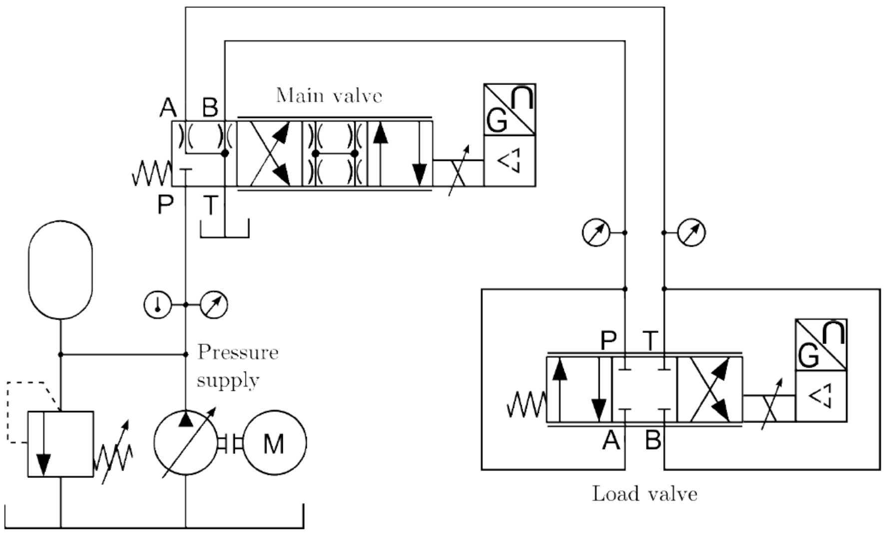

Figure 6: Experimental setup - proportional valve

4.1. Experimental hardware setup

Static and loads at the working ports of the main valve are imposed by actuation of a secondary proportional valve that connects the ports A and B of the main valve (see **Figure 6**). Due to the connection between the ports P and A resp. T and B of the load valve it operates only as throttle with a variable resistance hydraulic flow. The operating conditions in terms of load are affected by the system pressure and the dynamic secondary load valve position. The system pressure determined in terms of the pressure supplied by the pump is kept constant throughout a single evaluation but varies across evaluations of alternative conditions across a range between 0 and 200 bar. However, the load becomes dynamic by actuating the secondary valve reference position with the type of disturbance signals described in **Section 2**.

The operating conditions are optimized and compared in two different scenarios: a regulation problem in which the main controller maintains a constant valve position and a tracking problem in which the primary valve position tracks a stimulus composed of a step sequence. In both cases the affect of the disturbance on the regulation and tracking error is observed and analyzed.

4.2. Load disturbance for a regulation control problem

In this scenario the main valve controller regulates a static valve position at an opening of 50 % while its load is subject to a disturbance across a period of 250 ms. Two disturbance signals, namely a rectangular and sinusoidal load profile are investigated. The performance of the closed loop control is defined in terms of the integral of the squared error (ISE) between the actual and the command position. Hence, the scalar evolution strategy identifies those operating conditions as critical that maximize the ISE or minimize its negative value. An evolutionary run evolves a population of 50 solutions across 50 generations resulting in a total of 2500 fitness evaluations.

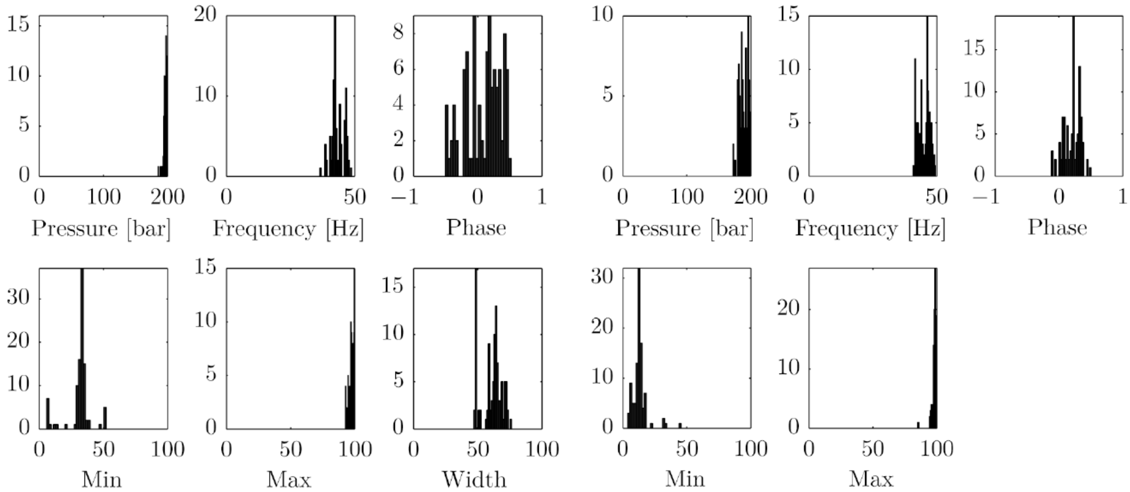

Figure 7: Parameter histograms for rectangular (left) and sinusoidal disturbances (right)

The distributions of the parameters of the solutions in the final generation are shown in **Figure 7** for the rectangular signals (left) and the sinusoidal signals (right). In case of scalar optimization, the algorithm converges towards a single optimal solution. It is apparent that most parameters converge to a narrow range among the solutions in the final generation. Thus the fitness of the optimal solution is highly sensitive with respect to these parameters. Other parameters such as the phase exhibit a wider range, thus their impact on the fitness is less critical. Taking a closing a closer look at individual parameters reveals the following observations. The maximum system pressure most critically effects the regulation error. In both cases the most critical frequencies of the disturbance are in the range between 40 Hz and 50 Hz at which the most energy is transmitted via the hydraulic. Higher frequencies in the reference signal of the load valve are dampened as the secondary valve acts as a low pass filter with respect to the hydraulic flow generated by actuation of the piston. The phase of the signal bears no relevance which is not surprising for a regulation problem in which there is no interference between the constant reference and the load. The most critical minimum (*Min*) and maximum (*Max*) amplitudes of the disturbance signal are such that they generate a maximal variation of the hydraulic flow. This is accomplished by attaining an upper limit (*Max*) at which the valve is fully opened. The minimal amplitude is located at about 30 % of the overall range for the rectangular signal and at 20 % for the sinusoidal signal. Full closure of the valve completely shuts down the hydraulic flow and thus the disturbance. The utilization of the valve piston amplitude of about 60 % of the overall range is the best compromise to maximize the amount of hydraulic flow as well as its variation thus generating a maximum disturbance entry.

4.3. Load disturbance for a tracking control problem

The disturbance of a tracking control problem introduces additional aspects in to the identification of critical operating conditions namely:

- multiple criteria in terms of the closed loop response for different step sizes and
- interference effects between the reference signal and the disturbance.

In this experiment the main valve tracks a reference signal composed of a sequence steps of different magnitude. The criterion integral of squared error (ISE) captures the transient as well as static closed loop behavior whereas the criterion maximal overshoot of the step response (MO) dominantly captures the transient behavior. In addition the closed loop response is distinguished for step signal in the medium (M) and large (G) range, thus resulting in overall four criteria (ISE_M, ISE_G, MO_M, MO_G). The two-dimensional projections of the four-dimensional approximation of the Pareto front resulting from the multi-objective evolution strategy are shown in **Figure 8**. The load signal is described in terms of the coefficients of a Fourier series. The crosses denote Pareto optimal solutions evaluated under the critical conditions in comparison to the criteria accomplished by the same controller in the undisturbed case. The negative sign of the criteria is due to the fact that the multi-objective evolution strategy by default minimizes objective functions.

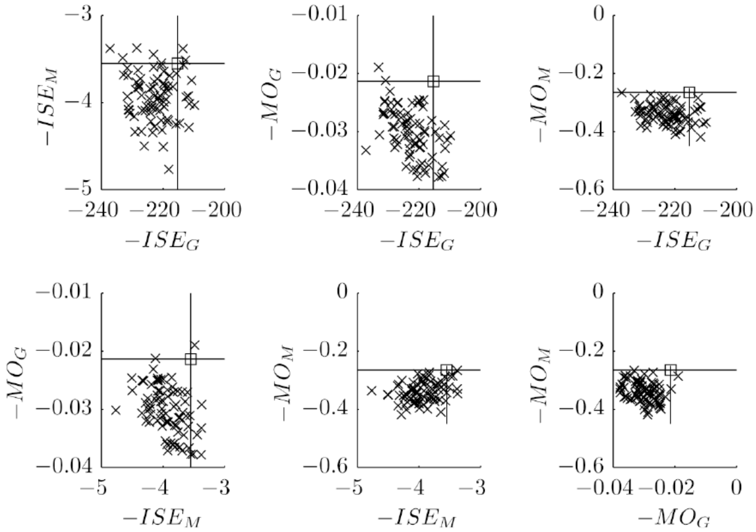

Figure 8: Pareto front for most critical disturbances for a tracking control problem

The Pareto optimal solutions capture the compromise between multiple conflicting objectives as shown in **Figure 9** which illustrates the disturbance signal for the load valve and the closed loop response of the main valve in reaction to the disturbance. For this particular disturbance the overshoot MO_G for the large step responses is severely enhanced. In particular the first large step in positive direction exhibits a significant overshoot and low damping of oscillations due to the interference between the disturbance and the reference signal at time t = 100 ms.

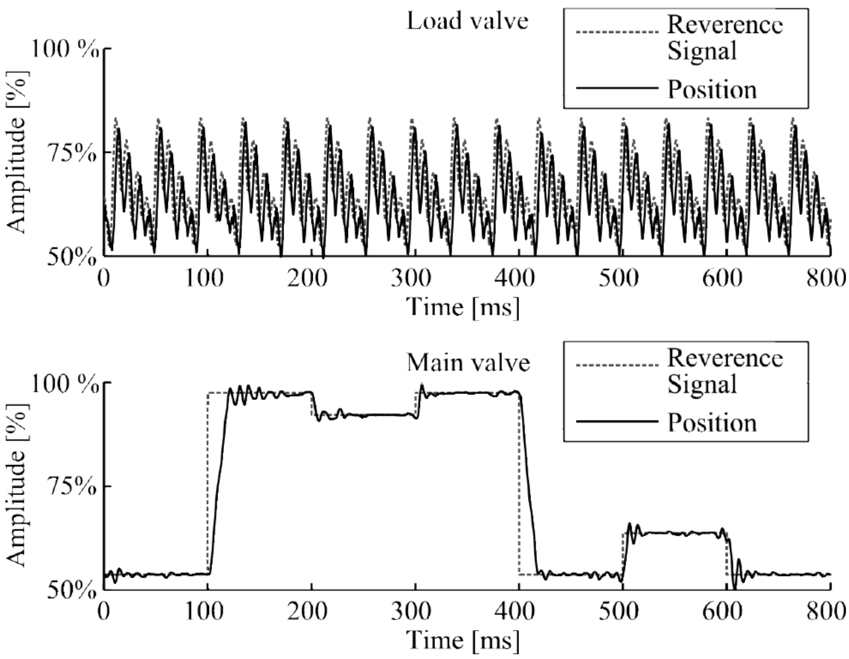

Figure 9: Disturbance signal and closed loop response for a particular critical operating condition

5. Conclusions

The experimental results demonstrate that the proper identification and selection of critical operating conditions is crucial for robust HIL evaluation and optimization of hydraulic valve controllers. The proposed approach enables the identification of worst case conditions and provides a qualitative picture of their detrimental impact on closed loop performance of the controller. This insight is helpful to enhance the experimental setup and strategy for a subsequent robust controller optimization by focusing on the most critical informative operating conditions. The controllers obtained from such a robust optimization are expected to exhibit verifiable performance across the entire operation envelope. This aspect of robustness is particular important in the context of hydraulic valves as they are integrated into highly diverse applications without adaptation of the underlying controller.

6. References

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