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Control of Pareto Points for Self-Optimizing Systems with Limited Objective Values ⋆

Jan Henning Keßler * **Ansgar Trächtler** *

* *Heinz Nixdorf Institute, Control Engineering and Mechatronics, University of Paderborn, Paderborn, Germany, (e-mail: {jan.henning.kessler|ansgar.traechtler}@hni.upb.de)*

Abstract: Self-optimization enables technical systems to adapt their behavior to varying environmental conditions and changing system settings. Objective functions serve as evaluation criteria for the system behavior. In this paper we propose a hierarchical control approach of an objective-based Pareto controller. We separate the processes of optimization and control. First, we use multiobjective optimization to compute a Pareto set of optimal system configurations offline. This set serves as a data base for the Pareto controller in an upper control loop, which is designed secondly. The goal of the Pareto controller is to drive the system toward a desired relative weighting of the objective values, despite unknown and varying environmental disturbances. Furthermore, the Pareto controller has to cope with limits of the objective values. For that, we propose a calculation of a reference value, which is based on an approximated Pareto front of the current situation. The Pareto controller selects suitable configurations out of the Pareto set and applies them to a lower control loop. A test rig of an active suspension system affected by unknown track excitations serves as application example. Finally, we give some results with the test rig that validate our approach and point out the advantages.

Keywords: Pareto optimal control, hierarchical control, multiobjective optimization, self-optimization, active suspension system

1. INTRODUCTION

Intelligent technical systems have the ability to adapt their control structure and parameters to varying environmental conditions and changing system settings at runtime. This feature is introduced as Self-optimization within the Collaborative Research Center 614 – Self-Optimizing Concepts and Structures in Mechanical Engineering (cf. Frank et al. [2004] among others). Objective functions serve as evaluation criteria for the self-optimizing system's behavior. In order to exploit the possibilities opened up by self-optimization, multiobjective optimization has been proven to be an effective technique for computing Pareto optimal configurations, see Geisler et al. [2008] and Schütze [2004] among others. As the objectives typically contradict one another, the solution of a multiobjective optimization problem is given by a set of optimal compromises, which is called Pareto set (cf. Hillermeier [2001]).

The optimal system configurations can be computed online at runtime or offline at design time. Model Predictive Control (MPC) approaches solve an optimization problem over a finite horizon within the closed control loop, see Camacho and Bordons [2004] and Mayne et al. [2000] among others. MPC approaches usually are based on simplified optimization models of the system and its objective functions, in order to solve an optimal control problem with minimal computational cost. In Vöcking and Trächtler [2008], Münch et al. [2008] and Esau et al. [2012], planning approaches are introduced, which use online simulations of forthcoming situations in order to select the best configurations out of the Pareto sets. For feedforward control approaches, the environmental disturbances have to be known exactly in advance. A simple linear-quadratic regulator (LQR) approach with a fixed parameter design is not able to control the objective values or at least their relative weighting. In Geisler and Trächtler [2009] the matrices of a classical LQR design are adjusted at runtime with respect to the current objective values. A drawback of adaptive LQR approaches is the restriction to simplified linear optimization models to guarantee an analytical solution. For many technical systems a LQR approach is neither useful nor applicable.

In this contribution we present a novel objective-based controller, which uses a Pareto set to control the system behavior within a superordinated control loop. In contrast to MPC approaches, we separate the processes of optimization and control. The multiobjective optimization process is executed offline, using a nonlinear optimization model of the plant and complex objective functions. The optimization model emulates the system behavior in detail. In such an approach, it is possible to compute the entire Pareto set in advance. Within a superordinated control loop we are able to select online suitable system configurations

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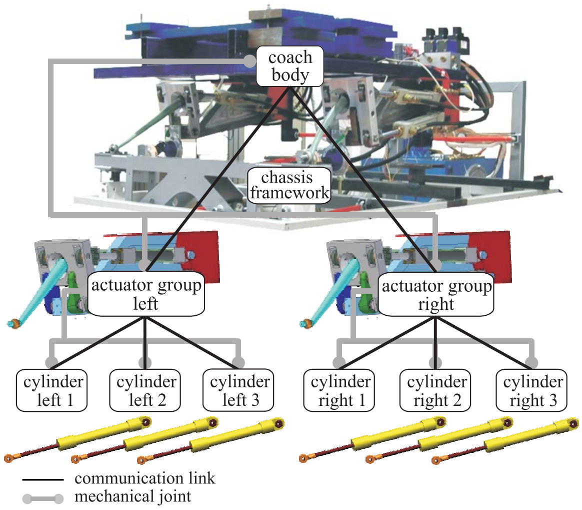

Fig. 1. Structure of the half-vehicle test rig.

out of the Pareto set. The main goal of this objective-based Pareto controller is to drive the system to a desired relative weighting of the objective values. We present how to continuously control the Pareto points, in order to react situationally on rapidly varying and unknown environmental disturbances, which affect the current objective values. In realistic scenarios the system has to cope with limits of the objective values, e.g., an upper limit of energy consumption. This demand has to be ensured within the objective-based Pareto controller. Hence, we propose a calculation of a reference value in objective space as an input for the Pareto controller in the superordinated loop, in order to satisfy the limits. Thus, we are able to control both the relative weighting of the objective values and the absolute value of one objective due to a given limit.

We present the active suspension system of the innovative railway vehicle RailCab (see Henke et al. [2008], RailCab [2013]) as an application example for the objective-based Pareto controller. An energy management system of the vehicle limits the available amount of energy for the active suspension system, e.g., in the case of a low state of charge. The suspension system performs the task of compensating for bumps and other excitations of the railway, in order to increase passenger comfort. There is a test rig which emulates the active suspension system of a half-vehicle, i.e., front or rear of the RailCab. The structure of the test rig is illustrated in Figure 1. It consists of a coach body which can move in vertical, lateral and rotational (body roll) degrees of freedom. Beneath the coach body there are two symmetrically mounted actuator groups (highlighted in Fig. 1), each one consisting of a guide kinematic, which is connected to the upper end of a GRP spring (glasfiber reinforced polymers) and three hydraulic cylinders. The main function of the actuator groups is to exert damping forces on the coach body by deflecting the GRP springs actively. A sky-hook controller is used to compute the damping forces (cf. Li and Goodall [1999]). It depends on three controller parameters p_i, $i \in \{1, 2, 3\}$, representing the damping characteristic of each degree of freedom of the coach body. At the lower end of the GRP springs there is a chassis framework that can again be displaced by three hydraulic cylinders. The chassis framework represents the environmental disturbances and it is used to simulate the railway excitations. These excitations vary continuously along the track and have high influences on the dynamic behavior of the coach body.

The paper is structured as follows: The theoretical background of multiobjective optimization and the application to the test rig are described in Section 2. In Section 3 we introduce the basic structure of the objective-based Pareto controller. We also point out the computation of a reference value for the Pareto controller considering a given limit of one objective values. We present the results with the real test rig in Section 4, which show the applicability of our approach. Finally, we conclude and give an outlook on future research in Section 5.

2. MULTIOBJECTIVE OPTIMIZATION

In this section we give a brief overview of the theoretical background of multiobjective optimization. Further, we present the application of multiobjective optimization for the active suspension system and we discuss the optimization results.

2.1 Theoretical Background

In the context of multiobjective optimization of mechatronic systems usually several objectives have to be considered and optimized simultaneously, e.g., minimization of energy consumption or maximization of performance. Mathematically speaking, this leads to a multiobjective optimization problem (MOP)

$$\min_{p}\{F(p) : p \in S \subseteq \mathbb{R}^{n_p}\}, \tag{1}$$

where F is defined as the vector of objective functions, $f_1, ..., f_k$, $k \geq 2$, which are at least continuous and S is the feasible set given by equality and inequality constraints, see Hillermeier [2001], and Ehrgott [2005] for a general introduction. Here, minimization refers to the comparison of vectors. A vector v_1 dominates another vector v_2, if all its entries are less than or equal to the entries of the other vector, i.e., $v_1 \leq_p v_2$. A point $p^\star \in S$ is called Pareto optimal for (1), if there is no $p \in S$ with $F(p) \leq_p F(p^\star)$ and $f_j(p) < f_j(p^\star)$ for at least one $j \in \{1, ..., k\}$. Thus, for contradicting objectives, the solution of (1) is not a single point, but a set of optimal compromises, which is called Pareto set P_S. The image of the Pareto set is called Pareto front P_F. In mechatronic systems the optimization parameters p are typically controller parameters or reference trajectories, e.g., controller gains or sampling points of a trajectory. The feasible set S is limited to parameters which can be implemented to the system and satisfy the stability criteria of the closed-loop system. These demands have to be evaluated in advance.

For the computation of the Pareto set we use numerical set-oriented methods, see Schütze [2004] and Dellnitz et al. [2005] for a detailed description. The objective functions of (1) are typically chosen as mean values of characteristic signals, i.e., they are given by integral functions

$$f_i : \mathbb{R}^{n_p} \to \mathbb{R}, f_i(p) = \frac{1}{T}\int_0^T h(y_e(p,t))\,\mathrm{d}t. \tag{2}$$

The evaluation of (2) is done by means of simulations of an optimization model. The vector y_e is the simulated output of the plant model and the function h respresents additional modifications, e.g., a weighting or filtering of the components of y_e. Using this optimization model, a generic reference situation of the system can be simulated, see Krüger et al. [2013] for more details. A large simulation time T is required in this simulations for the objective functions to converge to steady state values. The simulation time T depends on the system dynamic visible in the signal $h(y_e(p,t))$.

2.2 Application of Multiobjective Optimization

The purpose of the active suspension system is to increase passenger comfort by minimizing the accelerations of the coach body, while reducing the energy consumption of the actuator modules at the same time. Both objectives are contradicting because the more the coach body is damped, i.e., the accelerations are reduced, the more hydraulic power is needed. This leads to a MOP (1) with two objective functions, combined in the vector $F(p) = [f_1(p), f_2(p)]^T$. The system behavior can be adapted according to one objective by varying the three damping coefficients d_{sky} of the sky-hook controller. Thus for an optimization these controller parameters are also the optimization parameters p. The set of optimal parameters $p^\star$ are computed by means of solving a MOP offline. The objectives are given by the following integral functions

$$f_1 : \mathbb{R}^3 \to \mathbb{R},\ f_1(p) = \frac{1}{T}\int_0^T \sum_{j=1}^{6} P_{hyd,j}(p,t)\mathrm{d}t\,, \quad (3)$$

$$f_2 : \mathbb{R}^3 \to \mathbb{R},\ f_2(p) = \frac{1}{T}\int_0^T \sum_{i=1}^{3} |w_i(a_i(p,t))|\,\mathrm{d}t\,. \quad (4)$$

The equation (3) describes the average energy consumption given by the hydraulic power P_{hyd} of the six cylinders. A value of an average discomfort is computed by (4) considering the frequency weighted coach body accelerations a_i in the aforementioned three degrees of freedom. The weighting filters w_i are explained in VDI norm 2057 [2004].

The optimization is based on a complex nonlinear model, which emulates the test rig in detail (see Figure 1). The feasible set S of the three controller parameters p_i is restricted due to stability limits of the test rig. A band-limited white noise excitation profile is used as a synthetic environment model and emulates a common track profile with a wide range of typical track characteristics. The simulation time T is fixed to 3.5 seconds during one simulation of the optimization process. The large simulation time is required for the objective function evaluation of (3) and (4) to converge to steady state values along the track in order to calculate the best possible solution of the MOP.

The numerical solution of the MOP with its three optimization parameters p_i, i.e., damping coefficients d_{sky} of the sky-hook controller, is shown in Figure 3. The corresponding Pareto front is illustrated in Figure 2 and has the typical shape of MOPs consisting of two contradicting objective functions. Low damping coefficients d_{sky} at the one end of the Pareto set result in a high value of the discomfort, f_2, but a low value of the average energy consumption, f_1, in objective space. In contrast, high damping coefficients at the other end of the Pareto set lead to a low value of the discomfort and a high value

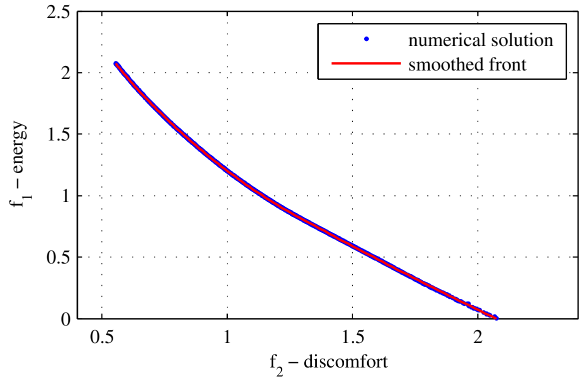

Fig. 2. Pareto front of the suspension system.

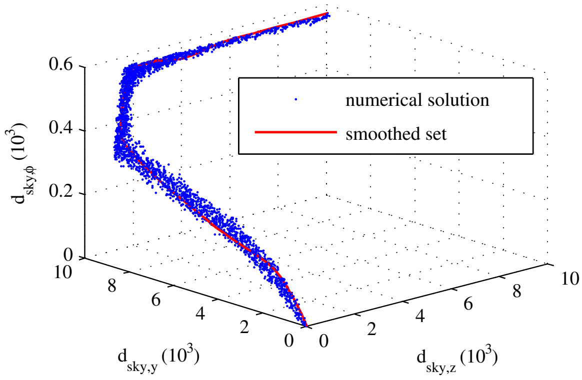

Fig. 3. Pareto set of the suspension system.

of the average energy consumption. The resulting system configurations in between are the optimal compromises of both objectives.

Usually the excitation profile varies along the railway and influences the dynamic behavior and also the objective values f_1 and f_2 of the system. This fact results in a separate MOP for each excitation profile. However, Münch [2012] shows the robustness of the Pareto set of the active suspension system in terms of varying magnitudes of the track excitation. In this context robustness means that the optimal parameters $p^\star$ of each MOP are practically identical. Nevertheless, the corresponding Pareto fronts of the robust Pareto set do not remain the same. For system operation, it is feasible to use one robust Pareto set, that is valid for a wide range of realistic track excitations.

In order to get a one-dimensional parameterization of the numerical solution, the Pareto set can be parameterized by a parameter α by means of the continuous and bijective function

$$s : \mathbb{R} \to P_S \subseteq \mathbb{R}^{n_p},\ \alpha \mapsto s(\alpha), \quad (5)$$

as illustrated in Figures 2 and 3. The parameter α is the relative weighting of the objective values, represented by the angle of the vector of the objectives. The Pareto front of the numerical solution and the smoothed front are almost congruent (cf. Fig. 2). The three-dimensional point cloud of the Pareto set can by approximated by (5) with sufficient accuracy (cf. Fig. 3). The limits of the feasible set S are reached within the optimization process. The parameterized smoothed set and front serve as a data base for the objective-based Pareto controller.

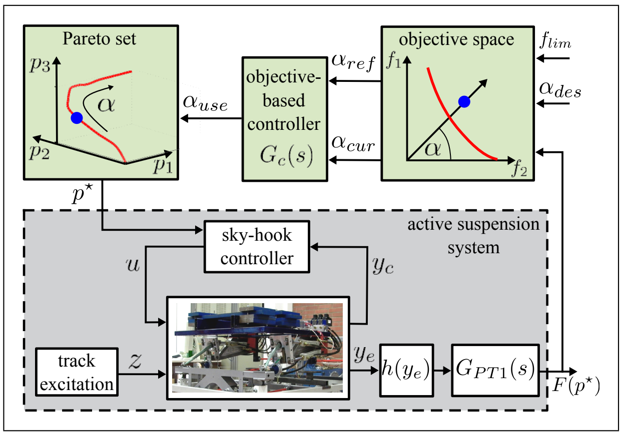

Fig. 4. Structure of the objective-based controller for the active suspension system.

3. PARETO CONTROLLER

The active suspension system pursues a compromise of the objectives, represented by the relative weighting α of the objective values. The main goal of the objective-based Pareto controller is to drive the system toward a specific desired relative weighting, despite the effects of environmental disturbances, which change unpredictably and continuously over time. Besides, the controller has to cope with limits of the objective values. In this contribution we treat an upper limit of the average energy consumption of the actuator modules as an example. Nevertheless, a lower limit is also conceivable, e.g., a minimum of passenger comfort. Therefor, we present both the basic approach on how to control points on the Pareto set in case of varying excitations and the computation of a reference value of the relative weighting considering a given limit of the average energy consumption, i.e., objective value f_1.

3.1 Basic Pareto Controller

The structure of the objective-based Pareto controller of the active suspension system is illustrated in Figure 4. It is a hierarchy of two control loops. The lower control loop comprises the plant, i.e., the test rig of the suspension system, and the configurable sky-hook controller with the three damping coefficients d_{sky}. The task of the lower control loop is to ensure a desired damping characteristic. Varying environmental disturbances z of the track have high influences on the dynamic behavior of the suspension system and lead to heavy fluctuations of the coach body's accelerations and the energy consumption of the hydraulic cylinders. With an arbitrary optimal parameterization $p^\star$ of the sky-hook controller, the current objective values $F(p^\star)$ and their relative weighting α fluctuate as well.

The upper objective-based Pareto controller continuously adjusts the optimal parameters $p^\star$ of the lower sky-hook controller, in order to control the current objective values $F(p^\star)$. Hence, an online evaluation of the objective functions is required. The use of the integral functions (3) and (4) of the optimization process leads to a discrete execution of the upper control loop with a sample time of several seconds, as presented in Krüger et al. [2013]. As a result, the parameters of the lower control loop are constant during each sampling period. This leads to a poor performance of the Pareto controller in case of intensively varying track excitations z. In order to react more quickly on unpredictable and continuously varying excitations, it is necessary to evaluate the objective functions continuously at runtime. The calculation of the objective values is divided into two parts (cf. Fig. 4): The function $h(y_e)$ computes the relevant data for the objective functions based on the measurements y_e of the suspension system. Further, we use a first-order lowpass filter as an appropriate approximation of the objective values, instead of the integral functions (3) and (4). The filter computes an average value of the signal $h(y_e(t))$ over a preceding horizon. The transfer function of this filter is given by

$$G_{PT1}(s) = \frac{1}{T_{lp}\, s + 1} \,. \tag{6}$$

The time constant T_{lp} is chosen as 0.5 seconds with respect to the slowest dynamic of the lower loop. The high-frequency signal parts visible in the measurements y_e, e.g., peaks of the hydraulic power of the cylinders, are suppressed. The initial value of the filter is set to the offline computed solution of the MOP (cf. Figure 2).

The current objective values $F(p^*)$ are mainly affected by the unknown track excitations z. In general, the higher the magnitude of the excitation, the higher the acceleration of the coach body and the energy consumption of the actuator modules. Thus, the objective-based Pareto controller is not able to drive the objective values to an arbitrary point in objective space. Hence, the current objective values $F(p^*)$ are transformed to a current relative weighting in objective space, α_{cur}. The α_{cur} value serves as control variable to the objective-based Pareto controller in the upper loop. The controller $G_c(s)$ is realized as a linear SISO (single-input, single-output) controller. In combination with a reference value of the relative weighting, α_{ref}, the controller computes the α_{use} value. The controller is proposed to be a PI-controller with the transfer function

$$G_c(s) = K_p + K_i\, \frac{1}{s} \,, \tag{7}$$

so that the steady state error is zero. For the active suspension system the controller parameters are set to $K_p = 4$ and $K_i = 12.5$. The controller design has to be considered separately and is not topic of this contribution (cf. Krüger et al. [2013]). The computation of the α_{ref} value is described subsequent. Finally, optimal sky-hook controller parameters $p^\star$ are selected out of the parameterized Pareto set by means of the α_{use} value. Then, these parameters are continuously set to the lower loop.

3.2 Computation of the α_{ref} Value

In realistic scenarios the active suspension system has to cope with a limited amount of energy. One can imagine that a superordinated energy management system of the vehicle limits the available energy due to a low state of charge of the energy storage, for example. This demand must be ensured within the computation of the reference value α_{ref} in the upper loop.

The computation of the α_{ref} value in objective space is schematically shown in Figure 5. As already mentioned, the values of the current objectives $F(p^*)$ are affected by the unknown excitation z. The points in objective

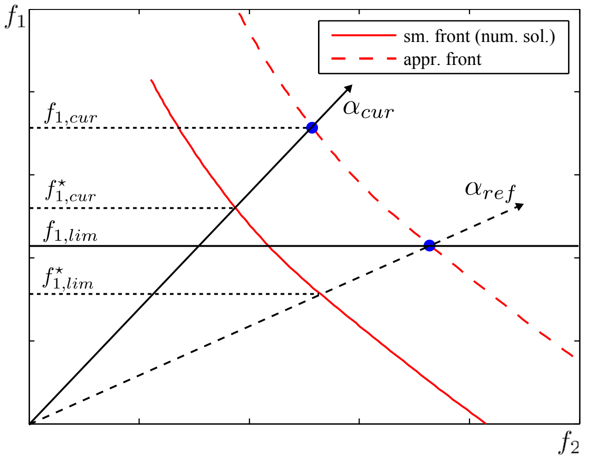

Fig. 5. Scheme of the computation of the α_{ref} value in objective space.

space depend on the magnitude of the excitation and the present configuration $p^\star$. In the event illustrated, the current objective value $f_{1,cur}$ is higher than the objective value $f^\star_{1,cur}$ of the Pareto front referred to the current relative weighting α_{cur}. This implies that the magnitude of the current excitation is higher than the one of the synthetic excitation model of the optimization process. Without knowing the numerical solution of the MOP of the current event, we assume a similar shape of the approximated Pareto front to the smoothed Pareto front of the numerical solution, as shown in Figure 5 (cf. Münch [2012]). The current objective values, $f_{1,cur}$ and $f_{2,cur}$, are restricted to points on the approximated front due to the current magnitude of the excitation z. Considering a lower limit value $f_{1,lim}$ of the average energy consumption, both objective values could be at best at the intersection point of the approximated front and the limitation line (cf. Fig. 5). The relative weighting of this point serves as the reference value α_{ref} for the objective-based Pareto controller in the upper loop. In order to compute the α_{ref} value, we can use the theorem of intersection lines. For that, we have to calculate the corresponding $f^\star_{1,lim}$ value of the numerical solution by

$$f^\star_{1,lim} = f_{1,lim}\,\frac{f^\star_{1,cur}}{f_{1,cur}}\,. \tag{8}$$

Then, the reference value α_{ref} is uniquely defined by

$$\alpha_{ref} = s^{-1}(f^\star_{1,lim})\,, \tag{9}$$

where s^{-1} is the inverse function to (5). In this event, the goal of the objective-based Pareto controller is to drive the current objective value $f_{1,cur}$ toward the upper limit $f_{1,lim}$. As a consequence of contrary objectives, the objective value f_2, i.e., low coach body accelerations, becomes worse due to the adherence of the upper limit of energy consumption (cf. Fig. 5).

3.3 Switching Logic at Runtime

The current objective values $F(p^*)$ are computed continuously at runtime by an appropriate approximation with a first-order lowpass filter. The points in objective space vary and depend on the current magnitude of the excitation z, which changes rapidly over time. Now, two cases must be distinguished in terms of the computation of the reference

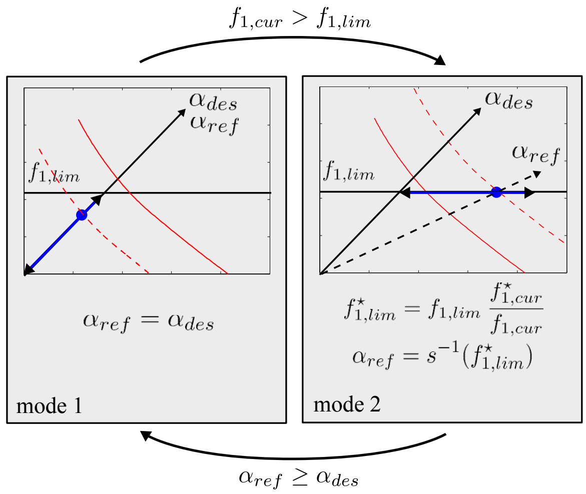

Fig. 6. Switching logic for the α_{ref} value.

value α_{ref} at runtime. For that, there exist two operation modes and switching conditions, illustrated in Figure 6.

In mode 1, we consider the case that the current objective value $f_{1,cur}$ is less than a given limit value $f_{1,lim}$. In this case, the reference value α_{ref} is equal to a desired relative weighting α_{des}. The α_{des} value and the $f_{1,lim}$ value are given by an external source, e.g., by a superordinated vehicles management system or by the user (cf. Fig. 4). The objective-based Pareto controller drives the current relative weighting α_{cur} toward the desired relative weighting α_{des}. If the magnitude of the excitation z increases, the current objective value $f_{1,cur}$ increases as well, until it exceeds the limitation value $f_{1,lim}$. Within the controller structure of the upper loop the reference value α_{ref} switches situationally from the constant desired relative weighting α_{des} in mode 1 to the value of the relative weighting considering the energy limit $f_{1,lim}$ in mode 2. In that case, the switching condition from operation mode 1 to operation mode 2 is straightforward, given by the inequality $f_{1,cur} > f_{1,lim}$ (see Fig. 6). In operation mode 2, the $f^\star_{1,lim}$ value and the α_{ref} value are calculated continuously by (8) and (9). If the magnitude of the excitation z still increases, the current objective value $f_{2,cur}$ becomes worse. In contrast, if the magnitude decreases, the current objective values $f_{2,cur}$ becomes better. The reverse switching condition from operation mode 2 to operation mode 1 is not as obvious as in the first case. It is not sufficient to consider only the $f_{1,cur}$ value, i.e., $f_{1,cur} \leq f_{1,lim}$, because the current objective value $f_{1,cur}$ runs within a small range around the upper limit due to the unknown and continuously varying excitation z and the predefined assumptions. This would result in a high-frequent switching rate with unintended steps in the α_{ref} value. Thus, we treat the continuously computed relative weighting itself for the reverse switching condition. Here, the switching condition from mode 2 to mode 1 is defined by $\alpha_{ref} \geq \alpha_{des}$ (cf. Fig. 6), in order to get a continuous reference value α_{ref} as an input for the Pareto controller. In that case, the inequality $f_{1,cur} \leq f_{1,lim}$ is implicit.

4. RESULTS

In this section we show the practical results of the objective-based Pareto controller with the test rig of

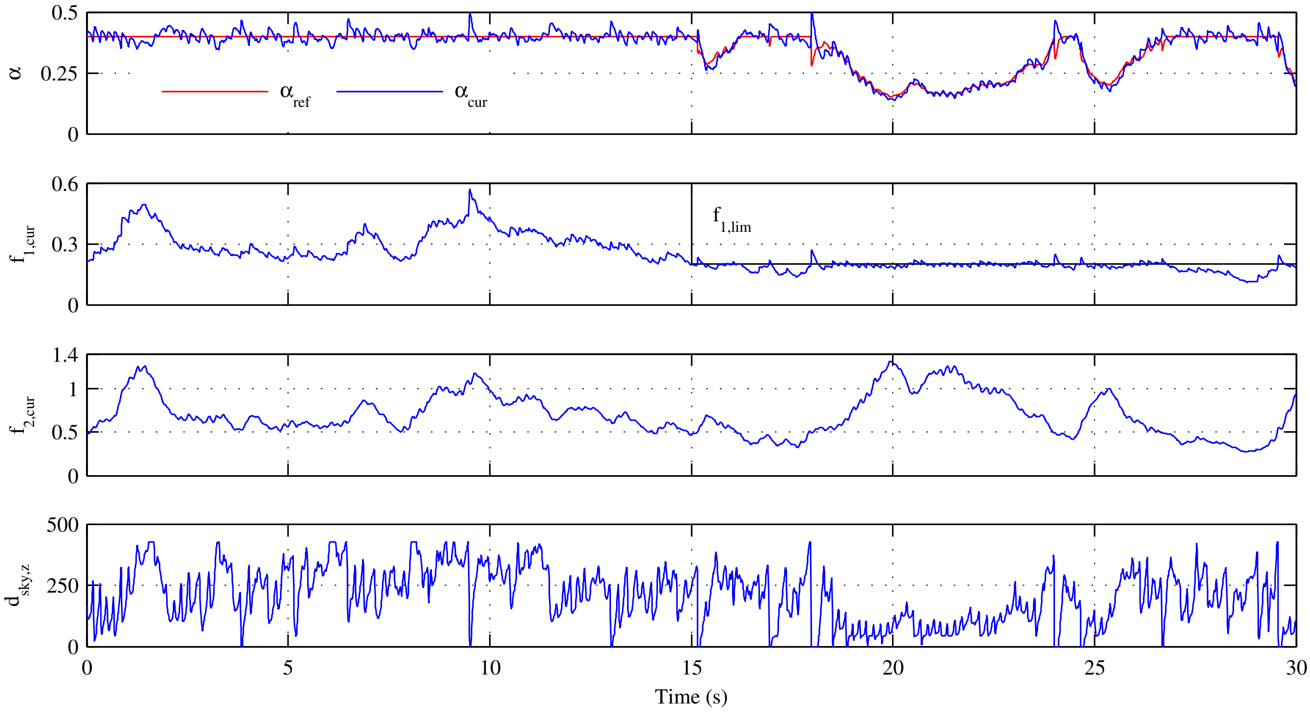

Fig. 7. Test rig results of the reference and current relative weighting α_{ref} and α_{cur}, the approximated objective values $f_{1,cur}$ and $f_{2,cur}$, and the sky-hook controller parameter $d_{sky,z}$ in vertical direction.

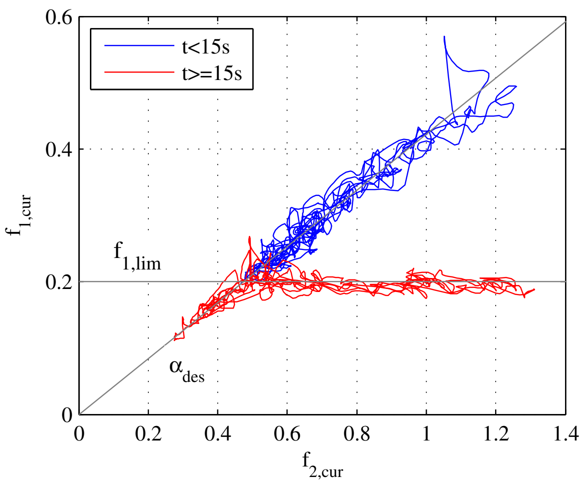

Fig. 8. Trajectory of the current objective values $f_{1,cur}$ and $f_{2,cur}$ in objective space.

the active suspension system. The objective-based control strategy is applied to a realtime hardware, using the configurable sky-hook controller of the lower loop and the Pareto controller of the upper loop. The excitation scenario used for test rig operation is based on a virtual track, which contains excitations in each of the three degrees of freedom of the chassis framework. These excitations are generated stochastically, but describe a realistic track profile along the railway.

The test rig results are shown in Figures 7 and 8. Figure 7 illustrates the reference and the current relative weighting α_{ref} and α_{cur}, the corresponding current objective values $f_{1,cur}$ and $f_{2,cur}$, and the sky-hook controller parameter $d_{sky,z}$. Figure 8 shows the current objective values in objective space. The main task of the objective-based Pareto controller is to drive the system toward the desired relative weighting α_{des}. In this scenario the α_{des} value is set to 0.4. From beginning of the measurement to 15 seconds the system is in operation mode 1 (cf. Fig. 6) due to no limits of the objective value f_1. Thus, in mode 1 the α_{ref} value is equal to the α_{des} value. Until 15 seconds the Pareto controller is able to keep the α_{cur} value within a small range of the α_{ref} value. The current objective values lie close to the straight line of the desired relative weighting α_{des}, as shown in Figures 7 and 8. The slight fluctuations of α_{cur} can not be completely compensated for, because they are the result of the unknown track excitations. The approximated objective values $f_{1,cur}$ and $f_{2,cur}$ fluctuate as well due to a varying magnitude of the track excitation over time. The three sky-hook controller parameters d_{sky} are selected out of the smoothed Pareto set and they are continuously set to the configurable controller of the lower loop. Exemplarily the corresponding sky-hook controller parameter in vertical direction $d_{sky,z}$ is shown in Figure 7.

At 15 seconds the limit value $f_{1,lim}$ of the objective value f_1, i.e., a limit of the average energy consumption of the system, is set to 0.2. From that moment the system switches situationally from operation mode 1 to operation mode 2 and reverse due to the magnitude of the current objective values and their relative weighting. From 15 seconds to 30 seconds the reference value α_{ref} is less than the desired relative weighting α_{des} over large periods, as shown in Figure 7. In that cases, the system is in operation mode 2 and the reference value α_{ref} is calculated continiuously by (8) and (9). In operation mode 2 the Pareto controller is able to keep the current objective value $f_{1,cur}$ within a small range of the limit values $f_{1,lim}$ (cf. Fig. 8). From approximately 18 seconds to 23 seconds the magnitude of the track excitation is increased. In this period the Pareto controller calculates low α_{ref} values and selects low sky-hook controller parameters out of the Pareto set, as shown in Figure 7. As a consequence the current objective value $f_{2,cur}$, i.e., the value of discomfort, becomes worse. However, the reverse switching from operation mode 2 to operation mode 1 is clearly shown at approximately 27 seconds. From 27 seconds to 29 seconds the current objective value $f_{1,cur}$ is less than the limit value $f_{1,lim}$ and the reference value α_{ref} is again equal to the α_{des} value of 0.4. Now, the current objective values lie close to the straight line of the desired relative weighting α_{des}. The adherence of the upper limit and the switching processes are plainly shown by the trajectory of the current objective values in objective space in Figure 8.

5. CONCLUSION & OUTLOOK

In this contribution we presented a hierarchical approach of a continuous objective-based Pareto controller for self-optimizing systems with limited objective values. At first, we presented the application example of the active suspension system and the results of the multiobjective optimization problem. The Pareto set and the Pareto front serve as the data base for the objective-based Pareto controller. Further, we have shown how to control a desired relative weighting of the objective values in case of unknown and varying track excitations, using suitable points of the Pareto set. The controller is also able to cope with limits of the objective values, represented here by an upper limit of the average energy consumption of the suspension system. We explained the calculation of a reference value of the relative weighting and the switching logic in objective space considering similarity relations of the Pareto fronts. Finally, the results with the test rig point out the applicability and effectiveness of our novel approach.

In future work a number of extensions are planned. To our experience, this approach seems to be realizable for a wide range of technical systems, because the proposed Pareto controller in the upper loop is almost independent of the underlying structure of the lower loop. Moreover, the control approach has to be enhanced to multiple Pareto sets, which are not robust in terms of varying environmental disturbances. It is also interesting to extend the approach to multiobjective optimization problems with more than two objectives. Since the parameterization of the Pareto set is then much more difficult, the controller structure in the upper loop has to be a more complex MIMO (multiple-input, multiple-output) controller.

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