# Cascaded Evolutionary Multi-Objective System Optimization for a Proportional Directional Control Valve

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IEEE/ASME International Conference on Advanced Intelligent Mechatronics, Auckland, New Zealand, 2018

# Cascaded Evolutionary Multi-Objective System Optimization for a Proportional Directional Control Valve

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***Abstract*— During the development of mechatronic systems hard- and software components are integrated into a single system. Mostly, a digital control concept is designed to control the interactions of the different sub-systems from different domains and to reach the desired system performance requirements. In the case of a proportional directional control valve, the closed-loop control response is used as a metric of the system performance. The performance can be either improved by optimizing the controller as well as the valve's hardware design parameters. When performing a holistic model-based system optimization, the optimization vector contains the controller and the hardware design parameters. A variation of the design parameters requires a time-consuming Finite-Element-Method (FEM) simulation. In contrast, the impact of different controller parameters on the system performance can be simulated with a low computational effort. Actually, following the control theory, the controller parameters must only be adjusted when the plant changes its characteristic. This contribution presents a cascaded evolutionary multi-objective optimization process which enables the subordinated controller design in the context of a holistic multi-objective system optimization of a directional control valve. The required optimization time decreases significantly since the outer optimization loop mainly focuses on the hardware improvement without the impact of the controller robustness. A real industrial application motivates the developed approach, but the cascaded process is evaluated more generally investigating well-known benchmark functions from the literature for multi-objective optimization.**

## I. INTRODUCTION

A holistic model-based system optimization process allows overcoming the shortcomings of serial product development. In this case, the interactions of the different subsystems from different domains of mechatronic systems can be evaluated and improved during an early development stage. In contrast, a mainly independent component development characterizes the serial approach. It aims to improve the system performance by optimizing the individual subsystems like maximizing the force and minimizing friction, regardless of the closed-loop behavior. The objective of the serial development of the directional control valve is the achievement of characteristic hydraulic values with strict consideration of safety aspects. The design process requires domain-specific simulation tools like the Finite-Element-Method (FEM) and the Computational Fluid Dynamics (CFD) in combination with human expertise. Finally, after the development of the individual sub-systems is completed a suitable control concept is designed for achieving the desired performance of the mechatronic system. The challenges and problems of the serial development approach are for instance discussed in [1] and [2].

By utilizing a holistic model of the proportional directional control valve, the closed-loop performance can be simulated and evaluated without the need for assembling a real valve [3]. This evaluation is possible since the model approach is based on lumped parameters and thus achieves short computing times. Moreover, it reaches a high simulation quality. However, a suitable model for system optimization must further exhibit a high level of detail and strong physical interpretability. It is not possible to meet all requirements with a single model approach. A model appropriated for control applications features several model simplifications. The model parameters have a more mathematical and a less physical character. The dependencies between the parameters are often neglected for simplification reasons. Hence, a model with lumped parameters has a limited level of detail. A viable model-based system optimization can either be realized by applying co-simulation techniques or a suitable parameterization process for the model with lumped parameters. In the first case, time-consuming FEM or CFD models are coupled directly to the controller like in [4]. In the second case, the model for control applications is parameterized based on more detailed simulation results of FEM or CFD like in [3], [5]–[7]. The second approach reduces the demand for the time-consuming simulations. However, to realize an adequate system optimization and thus a proper virtual system development the time effort must be within an acceptable range. To develop a smart mechatronic system like the proportional valve multiple optimization loops are required with different model and optimization configurations. In the context of reducing the time effort of the holistic system optimization, the control concept and the controller design play an important role. To some extent, the tuning of the controller parameters already constitutes a kind of system optimization. A trivial approach would be to include the controller parameters into the overall optimization vector. This vector would contain valve design parameters like geometric dimensions of several components as well as numerous controller parameters. In this case, every variation of the vector is treated as a new individual which needs to be evaluated. Hence, the optimization algorithm has to deal with significantly higher complexity.

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The valve controller is a complex nonlinear PID controller with 24 coupled parameters. The proportional and integral amplifications are extended with nonlinear curves to cover the small and large signal operation ranges. The real controller design requires an automated evolutionary multi-objective Hardware-in-the-Loop (HiL) optimization with a high expenditure of time [8]. To reduce the controller design effort the native position controller of the directional control valve is replaced with a model predictive control (MPC) concept. MPC solves an optimal control problem for a moving horizon in every sampling interval utilizing a dynamic model of the plant [9], [10]. The first control input value of the optimal control sequence is applied to the plant. The advantage of using a model with lumped parameters as the basis of the system optimization is the possibility of applying this model as the prediction model of MPC. Whenever a design change is proposed the model with lumped parameters is parameterized again. Hence, the prediction model is always given inherently. This control concept achieves a design adaptive characteristic and reduces the number of free controller parameters significantly. In the case of the directional control valve, the complexity decreases from 24 to three parameters [11]. The gradient-free and sub-optimal model predictive trajectory set control (MPTSC) is chosen within the system optimization framework of the directional control valve [12]. MPTSC is real-time capable even for high sampling frequencies $f_\mathrm{s}$ and has been already tested successfully on a real valve with $f_\mathrm{s} = 10\,\mathrm{kHz}$ and a simplified model [13].

The idea of this contribution is to adopt the problem formulation of the holistic system optimization and to develop a cascaded evolutionary optimization procedure which is suitable for a wide range of general multi-objective optimization problems. It is intuitive to divide the optimization vector into an *outer* and an *inner* parameter set. The variation of the *outer* parameters initiates the simulation of the time-consuming FEM. The tuning of the *inner* set only requires the parameterized model with lumped parameters. This idea follows the control theory of redesigning the controller whenever the plant behavior changes. The solution which is presented here is motivated by a real mechatronic application similar to [14], [15]. Starting from a well defined multi-objective problem, a subordinated evolutionary multi-objective optimization is introduced for the *inner* parameters using the same objectives as the outer optimization loop. After the subordinated optimization is completed, the resulting *inner* Pareto front is transferred to the outer optimization loop. This approach aims to reduce the number of outer optimization iterations while reaching a pre-defined or desired optimization result. Since the outer set is related to the FEM, a lower overall computational effort is expected. Cascaded optimization strategies are known from the literature [14], [15]. However, they are primarily developed to handle the curse of dimensionality. To evaluate the performance and the necessary computation times well-known benchmark functions from the literature are used and extended to dimensions similar to the system optimization.

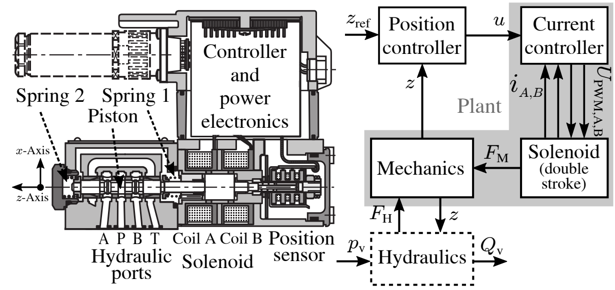


Fig. 1: Cross section of the proportional directional control valve 4WRREH6 [16]. The inner controller and the power electronics are treated as a part of the plant.

Section II describes the setup of the holistic model-based system optimization. Section III emphasizes the need for a subordinated multi-objective valve controller optimization. In section IV the developed cascaded optimization strategy is evaluated using benchmark test functions. Finally, section V summarizes the results and provides an outlook.

## II. Holistic Valve System Optimization

### *Proportional Directional Control Valve*

Figure 1 shows the cross section of the proportional directional control valve 4WRREH6 [16]. This valve routes oil from the pressure port P to the working ports A or B by moving the piston along the $z$-axis. The oil flow rate $Q(z(t), p_\mathrm{v}(t))$ is a function of the stroke $z(t)$ and the supply pressure $p_\mathrm{v}(t)$. The fast and precise stroke or position control is a challenging task since the valve has a fast-acting double stroke solenoid. Pre-loaded springs ensure the force-type connection of the movable valve parts. The inductive position sensor indicates a fully opened working port A or B with $z(t) = \pm 100\,\%$. In this contribution, only the complex outer position controller is replaced with MPTSC. The inner simple current controller and the power electronics are treated as a part of the plant and the prediction model. During the real controller design, the working ports A and B are closed, and the valve is filled with oil. Currently, hydraulic effects are not considered within the system optimization.

### *Parametrization and Optimization Process*

Figure 2 presents the overall and fully-automated system optimization process which was first introduced in [3]. An important part is the model with lumped parameters. The overall model describes the relationship between the control input $u(t)$ and the stroke $z(t)$. It contains a model for the solenoid and the mechanics which are modeled using the mass-spring-damper system with a nonlinear friction term. The overall valve model reaches a high simulation quality by applying Hammerstein model structures for the electromagnetic sub-systems. The modeling of the electromagnetic actuator is the main challenge. For this reason, a part of the solenoid model is shown in Figure 2. The characteristic solenoid curves represent the basic relationship between the current $i_\mathrm{A}(t)$ in coil A, the current $i_\mathrm{B}(t)$ in coil B, the stroke $z(t)$ and the static force $F_\mathrm{stat}(t)$. However, for instance a fast change of the current $i_\mathrm{A}(t)$ or $i_\mathrm{B}(t)$ initiates dynamic

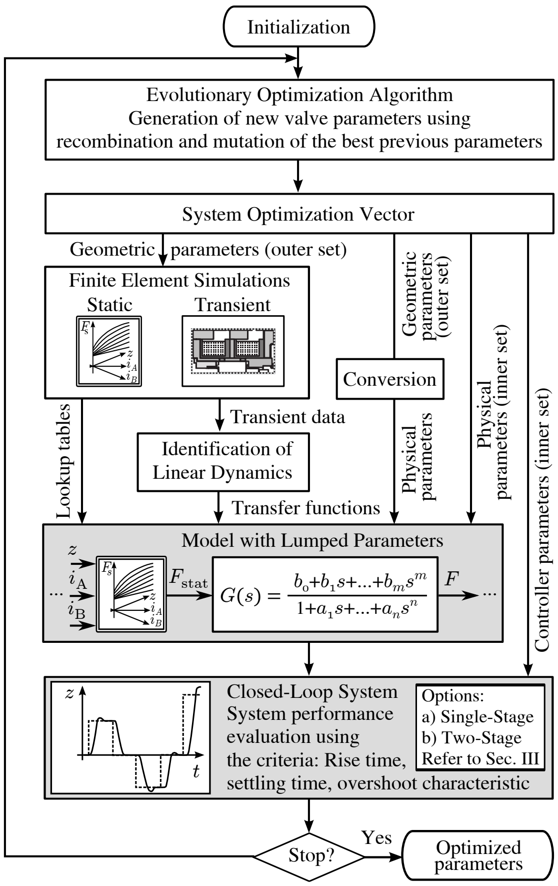


Fig. 2: Fully automated parameterization and optimization process of the holistic valve system optimization.

effects like eddy currents. The force value $F_{\mathrm{stat}}(t)$ predetermined by the characteristic curves is only available with $F(t)$ after a certain delay. The linear dynamics are applied to approximate dynamic effects. Usually, linear dynamics require less identification effort and data than nonlinear approaches. Further information regarding the model are reported in more detail in [3]. In the next step, the model with lumped parameters is parameterized using, inter alia, results of the FEM simulation. Since the solenoid is difficult to model with lumped parameters, the level of detail is increased for this sub-system. A 2D FEM model of the electromagnetic actuator is utilized. The characteristic curves result from a static FEM simulation. The linear dynamics are identified using a short simulated transient FEM signal. The new and intuitive parameterization process including the direct identification of dynamics differs from the static parameterization process in [7] and the application of reluctance networks in [5], [6]. Several geometric parameters like the number of coil turns can be transformed directly into physical ohmic resistance values. Further physical parameters like spring constants can be also treated as a part of the *inner* parameter set. The closed-loop performance is evaluated using the objectives rise time, settling time and overshoot characteristic. Thus, following the approach in [8] the optimization algorithm NSGA-II provides the evolution of the system's parameter values using recombination and mutation operators on the best previous parameters [17]. The resulting hardware parameters are feasible since the optimization is subject to a pre-defined parameter range and nonlinear constraints. For more information concerning the setup of the optimization algorithm refer to section IV.

## III. Evaluation of Closed-Loop Performance

Whenever the optimization algorithm in Figure 2 provides a variation of the optimization vector values, the parameterization of the model with lumped parameters is carried out. Hereby, the simulation of the FEM takes by far most of the parameterization time, approximately one hour with multiple threads. The simulation of the closed-loop system for a single inner parameter set requires only a few seconds. First, every optimization vector represents an individual which needs to be evaluated using several objective functions. Hence, to get the fitness of an individual the closed-loop system is simulated. To take the small and large signal performance into account, different step amplitudes of the reference position are commanded to the controller. The system optimization applies the following three criteria to evaluate an individual:

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

The rise times $T_{\mathrm{r},j}$ and the settling times $T_{\mathrm{s},j}$ are normalized to the reference performances $T_{\mathrm{r,ref},j}$ and $T_{\mathrm{s,ref},j}$. Since the reference exhibits no overshooting, the overshoot objective $Mo_{\Sigma}$ is calculated as a sum of the number of considered steps $v$. In this case, the optimization vector contains a slow *outer* set of eight geometric FEM parameters and a fast *inner* set of five parameters. The following two approaches with their advantages (+) and disadvantages (−) are possible to handle the time-consuming optimization:

a) Single-Stage: Every optimization vector variation is treated as a simple individual:
   − Design invariant variations of the optimization vector values enforce time-consuming FEM simulations
   − Convergence in an acceptable time is not expectable for a high number of optimization parameters
   + The standard optimization tool can be used
b) Two-Stage: Subordinated multi-objective optimization of the *inner* parameter set:
   − Selection of a an individual from a subordinated multi-dimensional Pareto front is difficult to automate
   + Reduces FEM simulation time significantly

In this contribution, the subordinated optimization is investigated (approach b.). Figure 3 shows the Pareto set of the subordinated optimization and for illustration a possible but randomly chosen individual of the single-stage optimization. This random individual highlights that just a single fitness test utilizing three objectives is performed during single-stage. In contrast, three individuals are chosen from the subordinated Pareto set and reviewed in the bottom plot of Figure 3. It can be seen that every non-dominated individual is superior in at least one criteria. During the real controller

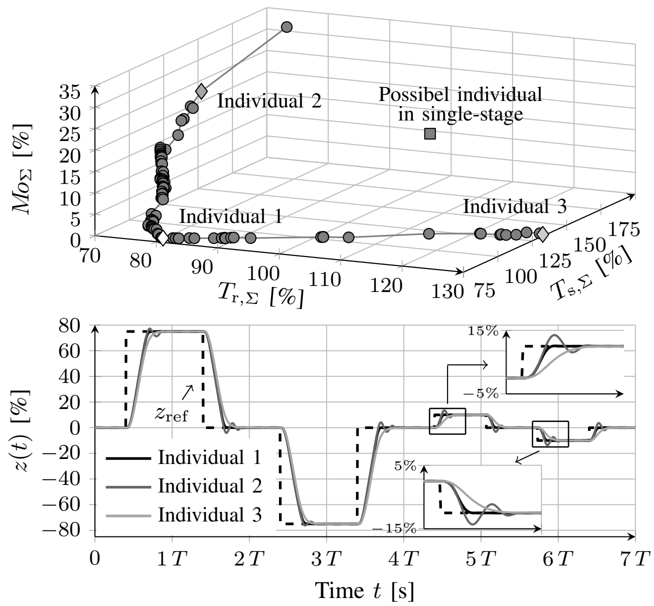


Fig. 3: Top: Pareto set of the subordinated optimization of the *inner* parameter set. Bottom: Different individuals of the Pareto set lead to non-dominated closed-loop performances.

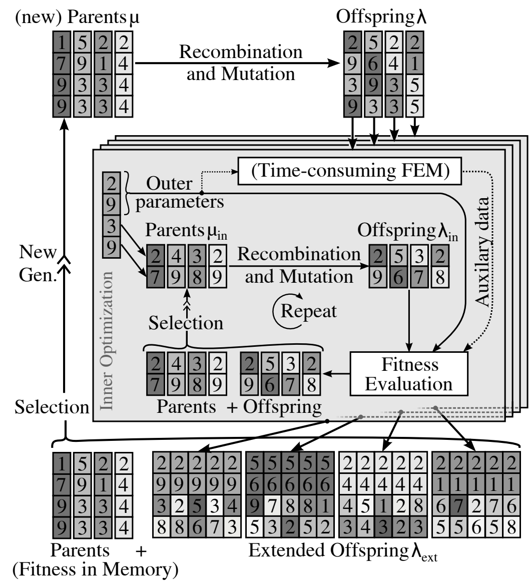


Fig. 4: Cascaded two-stage evolutionary optimization process for reducing the number of outer optimization loops.

design, the process expert would choose an individual subjectively which provides a good compromise between the overshoot and the rise time. Hence, it is difficult to automate the selection of an individual from the Pareto set or rather the mapping to a scalar optimization problem. The idea is to transfer the whole Pareto front to the outer optimization loop. The selection of a solution from the Pareto set should only be required when the system optimization is completed to define a prototype valve. Transferring the whole Pareto set means that every individual provided by the outer optimization loop, namely a FEM parameter vector, results in a new inner Pareto front. The next section presents this cascaded process.

## IV. Cascaded Evolutionary Optimization

Our framework employs a modified NSGA-II with continuous parameter operators [17], [18]. An important feature is the dominance based ranking scheme. The rank which is defined as $r_i = 1 + n_i$ is assigned to every evaluated individual. Hereby, $n_i$ denotes the number of dominant solutions according to the $i^{\mathrm{th}}$ individual. A tested individual is added to the Pareto set if it reaches the rank of one. If the Pareto set has more candidates than the pre-defined number of parents $\mu$, the density of the solutions is investigated. The so-called crowding distance penalizes and removes similar solutions. In this contribution, the $(\mu+\lambda)$-strategy is applied. Thus, the new parents are selected from the old parents $\mu$ and the offspring $\lambda$. An elite archive of the size $\eta$ is implemented to which the non-dominated solutions are transferred after selecting and storing non-dominated solutions. After the optimization reaches its termination criterion, the elite archive constitutes the Pareto set. For further information on evolutionary multi-objective optimization refer to [19]–[21]. Figure 4 introduces the cascaded optimization procedure. For clear illustration, the outer parents and offspring sizes are set to $\mu_{\mathrm{out}} = \lambda_{\mathrm{out}} = 4$, and the parameter values are rounded to integers. If choosing approach a) in section II, the extended offspring $\lambda_{\mathrm{ext}}$ would be equal to the offspring $\lambda_{\mathrm{out}}$. Since we apply approach b), the outer offspring parameters are divided into slow *outer* and fast *inner* parameters. Referring to the system optimization, the outer parameters constitute the design parameters of the time-consuming FEM simulation. For every outer offspring individual, an inner Pareto set is generated which is limited to $\eta_{\mathrm{in}}$. Therefore, an inner parents $\mu_{\mathrm{in}}$ and offspring size $\lambda_{\mathrm{in}}$ are chosen. However, for the inner fitness evaluation, the outer parameters and thus the FEM simulation results are necessary (auxiliary data). In this visualization, one outer optimization loop provides an extended offspring size of $\lambda_{\mathrm{ext}} = \lambda_{\mathrm{out}} \cdot \eta_{\mathrm{in}} = 4 \cdot 5 = 20$. This proposed cascaded optimization is straightforward since the outer and inner loop use the same objective functions. The outer loop parents are initialized with a random sampling strategy while the inner initial parents are generated utilizing a Gaussian sampling strategy depending on the provided outer parameter value ranges. The Gaussian sampling inherits the evolution progress from the outer into the inner loop.

A particular case of a cascaded evolutionary process is presented in [14] for the universal electric motor family problem. This paper aims to reduce the high dimensionality of the optimization problem starting from three objective functions and 88 parameters. The inner optimization is simplified to multiple independent optimization loops with two objectives and eight parameters each. To transfer the several inner results a fusion strategy for the numerous elite sets is developed, and the third objective function is evaluated after the fusion. In [15] a combination of an outer evolutionary and an inner particle swarm optimization algorithm is proposed to solve the universal electric motor family problem. Both developed solutions are ideal for this industrial problem.

In this contribution, benchmark test functions are chosen to evaluate the developed cascaded algorithm for two main reasons. On the one hand, the evaluation of the whole valve system optimization requires a comprehensive description of the setup and additional constraints. On the other hand, this contribution attempts to show the applicability of the strategy for common problems. Well-known benchmark test functions from the literature are extended to a similar dimensionality compared to the system optimization: Kursawe (KUR) with two objectives and $n = 12$ parameters $\mathbf{x}_{\mathrm{KUR}}$ and the parameter ranges $-5 \leq \mathbf{x}_{\mathrm{KUR}} \leq 5$ [22], Fonesca-Fleming function (FON) with two objectives and $n = 15$ parameters $\mathbf{x}_{\mathrm{FON}}$ and the parameter ranges $-4 \leq \mathbf{x}_{\mathrm{FON}} \leq 4$ [23], and FES3 with four objectives and $n = 10$ parameters $\mathbf{x}_{\mathrm{FES3}}$ and the parameter ranges $0 \leq \mathbf{x}_{\mathrm{FES3}} \leq 1$ [24]. Different partitions of the $n$ parameters with the inner $n_{\mathrm{in}}$ and the outer parameters $n_{\mathrm{out}}$ are assumed. First, the standard single-stage optimization with $\mu = \lambda = 100$ is carried out for 1000 generations to get a reference elite population. The resulting Pareto front is evaluated utilizing the $S$-Metric which is defined as the (hyper-)volume of the objective space between the elite individuals and a reference point [25]. Afterward, the required number of outer generations of the two-stage process is recorded. The aim is to reach the same $S$-Metric as in the case of the single-stage process. Figure 5 and Figure 6 present the evolution progress of the elite set for a two-dimensional objective space in the upper plots descriptively. The bottom plots show the course of the $S$-Metric over the generations and thus the convergence rate. The number of outer loop generations is used as a metric for the required computation time. The KUR Pareto set consists of a single individual and further eleven convex sections after 1000 single-stage generations. In the bottom plot, single representative evolution progressions are shown. The cascaded optimization converges much faster than the single-stage optimization. The more parameters are related to the inner set $n_{\mathrm{in}}$, the faster the $S$-Metric increases. The configuration of the inner loop is $\mu_{\mathrm{in}} = \lambda_{\mathrm{in}} = 50$ and $\eta_{\mathrm{in}} = 500$. The inner loop stops after 50 generations. Since KUR with 12 parameters is not easy to handle, and the initial outer population size is set to $\lambda = 100$, the two-stage optimization is in rare cases not able to reach perfectly the $S$-Metric of the single-stage process. However, the difference is neglectable, and the convergence rate is still much higher as in the case of the single-stage optimization. The dotted line in the bottom plot of Figure 5 is such a candidate. The FON problem produces a single coherent concave Pareto set. In this case, the cascaded strategy is even faster as for KUR. The configuration of the inner loop is $\mu_{\mathrm{in}} = \lambda_{\mathrm{in}} = 20$ and $\eta_{\mathrm{in}} = 200$. Note, the inner loop configurations are set up to provide a rapid improvement. They do not aim to reach dense Pareto fronts. Therefore, the outer loops are tuned to achieve high elite diversities. In the case of FES3 in Table I, the cascaded optimization outperforms the single-stage significantly. It requires less than 100 generations to reach the same performance regarding the $S$-Metric. The configuration of the inner loop is $\mu_{\mathrm{in}} = \lambda_{\mathrm{in}} = 20$ and $\eta_{\mathrm{in}} = 200$. Table I presents a statistical evaluation of the required generations of five runs of the two-stage process.

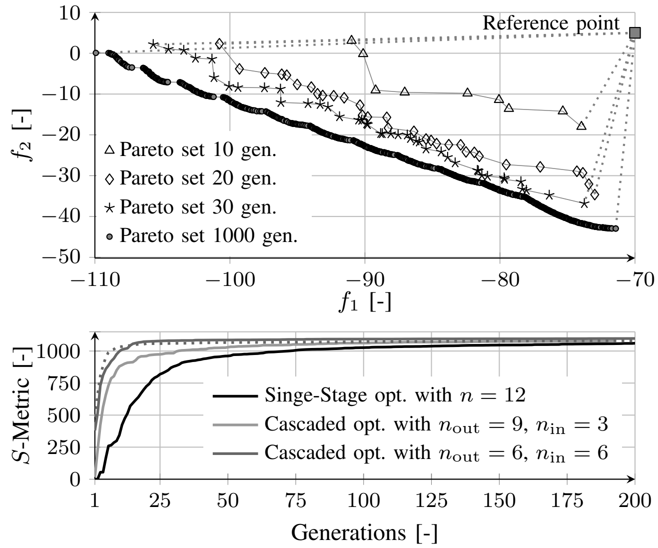


Fig. 5: KUR test function. Top: Different Pareto sets of the single-stage optimization. Bottom: Convergence of the single- and two-stage optimization concerning the $S$-Metric.

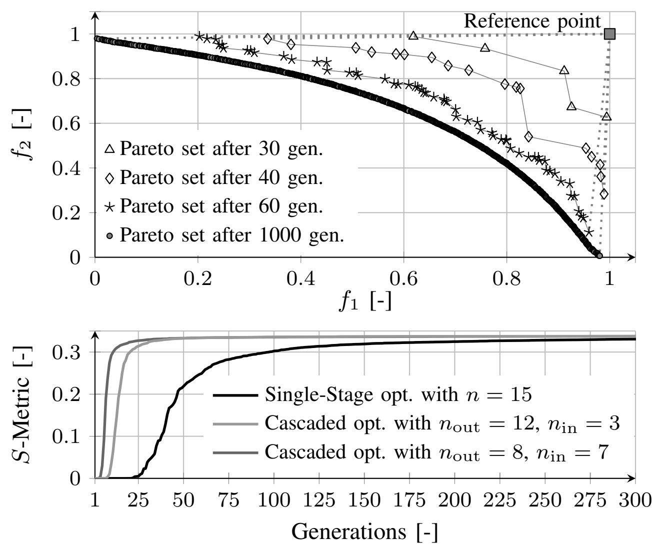


Fig. 6: FON test function. Top: Different Pareto sets of the single-stage optimization. Bottom: Convergence of the single- and two-stage optimization concerning the $S$-Metric.

Overall, the two-stage process requires (approximately) maximum half of the time or rather generations to reach the same results as the single-stage process (fifth column). In the cases of FON with $n_{\mathrm{in}} = 3$ and $n_{\mathrm{out}} = 12$ and FES3 the saving of computation times is immense. Hereby, the time effort can be reduced by at least 70 %. Referring to the motivated system optimization, the fast convergence behavior of the two-stage optimization plays a more important role. Until a prototype is developed plenty of different optimization runs with different configurations concerning the model and the algorithm setup are required. At the early stage of the system optimization, a fast convergence is desired. Moreover, the trend of the optimization vector is more important than the perfect approximation of the Pareto set since a model error is assumed in practice. The last two columns of Table I

TABLE I: Cascaded optimization results

| Benchmark, $[n_{\text{out}}, n_{\text{in}}]$ | No. of parameters $n$, objectives $n_{\text{f}}$ | Reference coordinates for $S$-Metric | Single-Stage $S$-Metric after **1000** generations | No. of required two-stage generations | Two-Stage $S$-Metric after **20** generations | No. of required single-stage generations |
|---|---|---|---|---|---|---|
| KUR, $[9, 3]$ | 12,2 | [-70,5] | 1107.7 | **446** $\pm$ 43 | 967 $\pm$ 49.3 | 58 $\pm$ 6 |
| KUR, $[6, 6]$ | 12,2 | [-70,5] | 1107.7 | **515** $\pm$ 22 | 1061 $\pm$ 9.2 | **198** $\pm$ 16 |
| FON, $[12, 3]$ | 15,2 | [1,1] | 0.3379 | **269** $\pm$ 41 | 0.2865 $\pm$ 0.0296 | 73 $\pm$ 5 |
| FON, $[8, 7]$ | 15,2 | [1,1] | 0.3379 | **401** $\pm$ 18 | 0.321 $\pm$ 0.0015 | **159** $\pm$ 5 |
| FES3, $[7, 3]$ | 10,4 | [6.8,7.4,9.4,1.7] | 71.656 | **70** $\pm$ 7 | 66.08 $\pm$ 1.22 | 204 $\pm$ 25 |
| FES3, $[5, 5]$ | 10,4 | [6.8,7.4,9.4,1.7] | 71.656 | **76** $\pm$ 8 | 66.75 $\pm$ 0.93 | **237** $\pm$ 35 |

highlight the significant difference between the single- and two-stage optimization after only 20 generations.

*Estimation of Required System Optimization Time*

If we assume a two-stage setup on a standard desktop PC, with $\mu = \lambda = 50$ for the outer loop during 20 generations, and $\mu_{\text{in}} = \lambda_{\text{in}} = 20$ for the inner loop during 20 generations, an optimization time of approximately three months ($t_{\text{opt},2} = 20 \cdot 50 \cdot 2\text{h}$) is estimated. One hour is assumed for evaluating a single outer individual and a full inner optimization in each case. The single-stage performances of the test-functions reach the $S$-Metric of the cascaded optimizations after 20 generations after at least 159 generations. Only a parameter division similar to the system optimization is investigated. Hence, the single-stage optimization would require approximately eleven months ($t_{\text{opt},1} = 159 \cdot 50 \cdot 1\text{h}$).

## V. CONCLUSIONS AND FUTURE WORK

A real industrial application motivates this contribution. The objective is to increase the valve's performance by optimizing controller parameters as well as hardware design parameters. Hereby, the optimization vector can be split into a slow outer parameter set which leads to time-consuming FEM simulations and a fast inner parameter set. The subordinated optimization of the inner parameter set requires only a short computing time and is inspired by the idea of performing a new controller design whenever the plant behavior changes. The overall aim is to reduce the number of time-consuming outer optimization loops of the evolutionary algorithm to save computing time. A cascaded evolutionary multi-objective optimization is introduced which is suitable for different benchmark test functions. Hence, the presented algorithm is generalizable to other multi-objective optimization problems. Future work is concerned with the evaluation of the system optimization of the valve in more detail.

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