# Using Desirability Functions for Many-Objective Optimization of a Hybrid Car Controller


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## ABSTRACT

In this work we investigated the concept of desirability functions for a many-objective optimization of a hybrid car controller with five objectives from different domains. We study this problem from the perspective of preference expression. Specifically we are looking at the impact of wrongly defined desirabilities and how this can be corrected using a Graphical User Interface (GUI). Overall we find that a desirability-based many-objective optimization approach could be well suited for real-world problems with objectives from many domains as it is becoming more and more common in industrial settings.



## KEYWORDS

Many-objective optimization, Desirability function, Car controller

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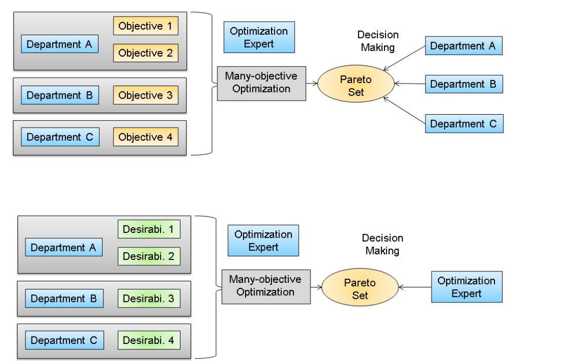


**Figure 1: Multi-criteria decision making process: (*top*) standard approach using domain-specific objectives, (*bottom*) usage of desirabilities to simplify decision making.**

## 1 INTRODUCTION

Industry increasingly faces many-objective optimization problems, which are even more challenging if objectives are from different technical domains and there is no expert for all domains available. Finding a proper compromise might then require an iterative decision making process between several specialist departments, see Fig. 1. In a recent paper [5] Wagner and Trautmann proposed a transformation of objectives using so called desirability functions that map all objectives into the range between zero and one. Desirabilities are easier to interpret for a non-expert and desirability functions (DFs) can be defined by an expert in the field without consideration of any other objective. Finally, since all objectives are in the same range and domain, they can more easily be combined, e.g. via geometrical or algebraic mean, into a single objective optimization or decision making process. This approach has so far been tested only on a small number of problems, e.g. [6], and we want to evaluate this approach on one of our optimization tasks, specifically the effect of unsuitable desirability function settings like unrealistic targets. These could lead, in combination with limited numerical precision, to a loss of gradient information due to the desirability transformation. We tested a Graphical User Interface (GUI) to online adapt desirabilities during the course of the optimization (similar to earlier work [3]).

Harrington et al. [2] proposed a Desirability Function (DF) which maps objective values to normalized desirability values. The closer the desirability score to one, the more satisfying the preference and the quality of the objective value. We chose Harrington's one-sided desirability function $d$ as a function of objective value $Y$, defined as $d(Y) = \exp(-\exp -(b_0 + b_1 Y))$, with $b_0$ and $b_1$ as control parameters for the desirability function. The Desirability Index(DI) is the scalarized (geometric or algebraic) mean of all desirabilities. We have used the relation to weighted hypervolume [1] to map desirabilities to preference vectors, allowing us to compare our approach to preference-based many-objective optimization methods.

Our application is a hybrid car controller optimization task [4]. It is a real-world optimization task with 5 objectives, non-trivial interactions between objectives and parameters, and a moderate run-time of the simulator (approximately one second). See Fig. 2 for a visualization of the hybrid car model including a list of parameters and objectives.

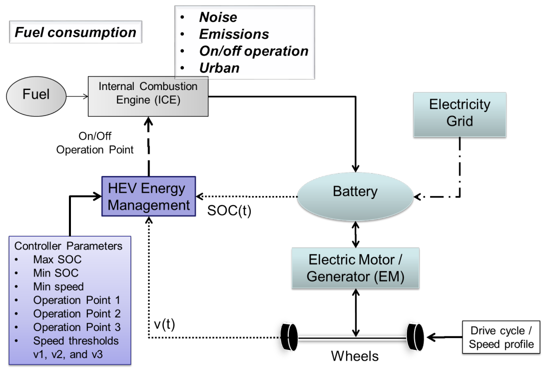


**Figure 2: Overview sketch of hybrid car control problem**

## 2 RESULTS

We analyzed the performance of the DF SMS-EMOA [5], a preference-based variant of the basic SMS-EMOA, for our application. We ran the basic SMS-EMOA and the DF version 20 times each and found that both mean and maximum HV values are quite similar, but noticed a much larger variability in final HV values for the DF version. Looking at the number of solutions dominating the preference solution we found that in 20 runs (2020 final solutions), there were 980 solutions dominating the preference solution for SMS-EMOA but 1275 for the DF-SMSEMOA, therefore the DF SMS-EMOA found substantially (30%) more solutions dominating the preference solution than the basic SMS-EMOA. These results are confirmed by boxplots of all objective values (Fig. 3) which show that for some objectives the DF version provides substantially better results relative to the preference solution.

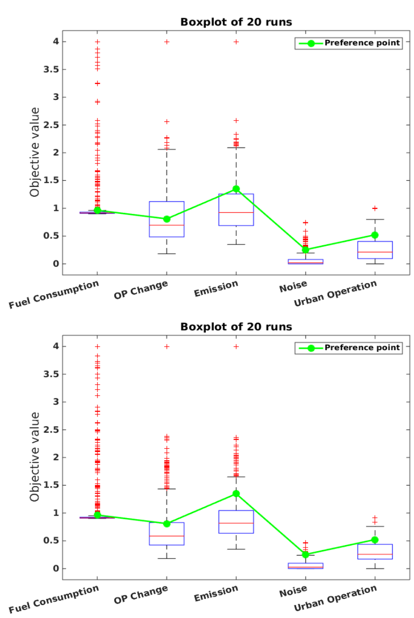


**Figure 3: SMS-EMOA (top) and DF-SMS-EMOA (bottom)**

We also investigated the effect of improperly defined desirabilities. In one example, we set extreme DF parameters by changing the shapes of DF to extremely high requirement levels. Objectives for which these extreme targets could not be reached, showed no progress as all desirabilities were equal. Consequently, population diversity (and HV) tends to decrease and we see no improvement of desirabilities for the affected objectives. This effect is the same if all DFs are changed to the opposite extreme. Since this effect can not always be anticipated before optimization, some online intervention is needed. In [5] a shift of the DF to lower requirement levels is performed if the median of the desirability distribution is below a threshold. Here we wanted to test if instead a voluntary decision of the optimization engineer could be used to solve this problem. We found that for changes to low requirements there is not much of a difference in the results compared to unchanged DFs. But if changing to higher requirements, we found a reduction in mean hypervolume values, and a larger number of solutions dominating the preference points.

## 3 SUMMARY AND OUTLOOK

We have investigated desirability-based preference expression for a real-world many-objective optimization problem. We found that sub-optimal preference settings might in extreme cases impair the optimizer. A GUI that visualizes the current state of the optimization and the distribution of objective values relative to the chosen DF parametrization was found to be very helpful to assess optimization progress and to trigger manual changes of desirabilities. Using DFs we saw a substantial increase in the number of found solutions that dominated the preference solution. Finally we tested the impact of a change in desirabilities in the middle of the optimization and found that the optimization can easily follow the new target setting. We conclude that desirability-based preference expression might be an interesting concept for complex many-objective optimization problems especially when single objectives are from different domains and hard to interpret.

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## REFERENCES

[1] Dimo Brockhoff, Johannes Bader, Lothar Thiele, and Eckart Zitzler. 2013. Directed multiobjective optimization based on the weighted hypervolume indicator. *Journal of Multi-Criteria Decision Analysis* 20, 5-6 (2013), 291–317.
[2] EC Harrington. 1965. The desirability function. *Industrial quality control* 21, 10 (1965), 494–498.
[3] Ben Paechter, RC Rankin, Andrew Cumming, and Terence C Fogarty. 1998. Timetabling the classes of an entire university with an evolutionary algorithm. In *International Conference on Parallel Problem Solving from Nature*. Springer Berlin Heidelberg, 865–874.
[4] Tobias Rodemann, Kaname Narukawa, Michael Fischer, and Mohammed Awada. 2015. Many-objective optimization of a hybrid car controller. In *European Conference on the Applications of Evolutionary Computation*. Springer, 593–603.
[5] Tobias Wagner and Heike Trautmann. 2010. Integration of preferences in hypervolume-based multiobjective evolutionary algorithms by means of desirability functions. *Evolutionary Computation, IEEE Transactions on* 14, 5 (2010), 688–701.
[6] K Wonggasem, T Wagner, H Trautmann, D Biermann, and C Weihs. 2013. Multi-objective Optimization of Hard Turning of AISI 6150 Using PCA-based Desirability Index for Correlated Objectives. *Procedia CIRP* 12 (2013), 13–18.