35th International Electric Vehicle Symposium and Exhibition (EVS35)
Oslo, Norway, June 11-15, 2022

Integrated Optimization of Fuel Cell Drive System Design and Energy Management

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Summary

This work describes a method for the automated design of fuel cell drive systems, enabling developers to identify ideal drive system configurations as well as suitable energy management strategies using multi-objective optimization. The authors focus on the integration of the energy management strategy optimization in the drive system design specification process and derive suitable approaches. These approaches are then evaluated regarding their optimization performance and the optimization results.

Keywords: fuel cell, fuel cell vehicle, optimization, research, simulation

1 Introduction

Legislators in multiple countries passed regulations aiming at a reduction of the greenhouse gas emissions of the transport sector [1, 2]. In addition to a lower overall traffic volume, an increased vehicle electrification is an important aspect regarding the reduction of emissions. Battery-electric vehicles (BEV) as well as fuel cell electric vehicles (FCEV) offer locally emission-free mobility. While BEVs to this day suffer from low perceived range and comparably high recharge duration, FCEVs combine the advantages of low refuelling duration and high operational range with the efficiency of electric traction motors. Thus, fuel cell drive systems are especially advantageous in applications for long-distance operations like semi-trucks [3, 4] although the first mass-produced and commercially sold FCEV has been introduced with the passenger car Toyota Mirai in 2014.

Proton exchange membrane fuel cells, the type of fuel cell commonly used in mobile applications, have some insufficiency regarding dynamics and cold start behavior. Furthermore, they do not enable regenerative braking. Therefore, fuel cell drive systems are hybridized by integrating a rechargeable electrical energy storage system (REESS), typically a battery. Because of this, fuel cell drive systems have some degrees of freedom during operation, e.g. the distribution of power and energy deployment between fuel cell and REESS, which are controlled by an energy management strategy (EMS). A properly optimized EMS ensures a high efficiency of the drive system and thus reduces the energy consumption of the vehicle. This paper presents and compares different approaches towards the integration of the EMS optimization during the fuel cell drive system design. The EMS used is an equivalent consumption minimization strategy (ECMS).

2 State of the Art

This chapter introduces the fundamentals and current state of the art of mathematical optimization methods, metrics to evaluate optimization results, electric drive system design approaches and energy management strategies.

2.1 Optimization

A multi-objective optimization problem is characterized by the presence of several objective functions, which must either be minimized or maximized. Usually, each objective is contradictory with at least one of the other objectives. Pareto optimality describes a state, when no individual solution can be further optimized towards one objective function without decreasing at least one other objective function. These solutions are also described as non-dominated, see Figure 1.

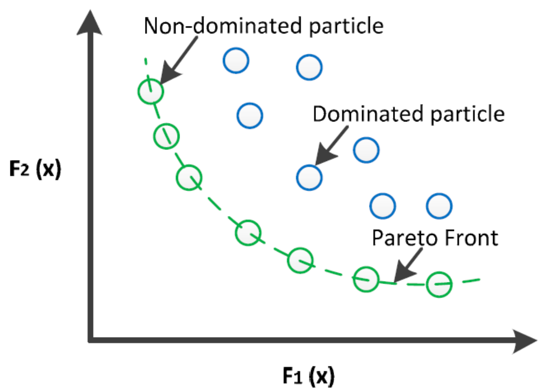

Figure 1: Pareto front, non-dominated and dominated solutions [5]

The simultaneous fulfilment of multiple objectives in one problem gives rise to a variety of such non-dominated solutions. Classical optimization methods suggest transforming the initial multi-objective optimization problem into a simple single-objective optimization problem, which minimizes the computation effort but requires the introduction of more subjective information to bias the solutions. More sophisticated approaches aim to find all solutions that belong to the Pareto front. These approaches are usually devised based on the imitation of biological or natural processes. Examples are Particle Swarm Optimization [6] and evolutionary algorithms, most notably genetic algorithms (GA) [ISS 7-10].

2.2 Optimization Quality

For the comparison of the multi-objective optimizations, a criterion is needed that objectively determines the quality of the results. The hypervolume is a suitable quality indicator as no prior knowledge of the Pareto front is needed. The hypervolume is calculated by comparing the Pareto front to a pre-determined closed hypervolume space. This hypervolume space is defined by two reference points spanning either a plane or three-dimensional space. An arbitrary number of sample points is uniformly scattered in the hypervolume space, forming a net. Each sample point is checked whether it is dominated by the Pareto front. The hypervolume is the ratio of sample points dominated by the Pareto front compared to the total number of sample points, see Figure 2. A higher value typically indicates a higher quality of the Pareto front as long as the reference points and number of sample points have been chosen properly for the given optimization problem. [12]

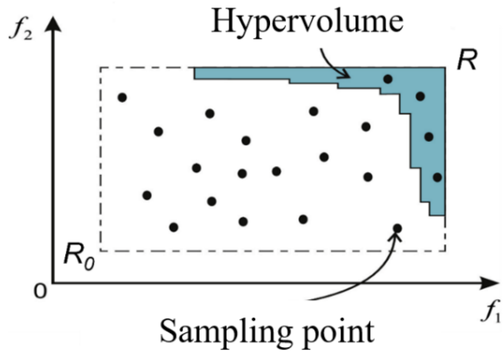

Figure 2: Hypervolume [11]

Other possibilities to compare and evaluate multiple Pareto fronts consist of a direct visual comparison (only suitable for two-dimensional Pareto fronts), the comparison of the number of individual solutions on the Pareto front as an indicator of convergence as well as the comparison of the crowding distances of the individuals on the Pareto front to evaluate their distribution.

2.3 Drive System Design

Because the components in fuel cell drive systems, aside from the fuel cell, are comparable to those in battery electric drive systems, this chapter first provides an overview of the state of research on design and optimization methods for battery electric drive systems before focusing on FCEV drive systems. As discussed in Chapter 2.1 of this work, numerous optimization methods can be used to perform single-objective or multi-objective optimization. [13]

For the design of battery electric vehicles, multiple single-objective optimization approaches have been developed. Aside from [14] and [15], the Electric Vehicle Identification (EVID) released in [16, 17] is a prominent methodology to determine the best drive topologies, component types and component characteristics of BEV. Several design parameters are modified and adjusted in order to enable customer-oriented design of electric drive systems in the early stage of product engineering. After that, the design objectives are assessed using a weighted sum function, with weighting variables determined from specific usage scenarios. [13] presents a multi-objective optimization-based holistic strategy. The advantages of multi-objective optimization are used to define a method for assessing the potential of several battery electric vehicle designs in terms of energy efficiency, driving dynamics, and cost.

In recent years, a large variety of design methods for FCEVs and fuel cell drive systems have been published. The authors of [18] describes one of the first systematic design methodologies for FCEV drive systems. Further research used several optimization methods, such as particle swarm optimization or dynamic programming, to focus on component sizing or cost-reduction in FCEV drive systems, and compared different optimization methods [19, 20]. Previously published design approaches for FCEV drive systems were enhanced by including the optimization of the energy management strategy in [21]. The design of fuel cell drive systems and associated energy management strategies is still a major focus of contemporary research. New methodologies for conceptual design of FCEV drive systems are given in [22, 23] utilizing full factorial design to identify optimal solutions. The author of [24] optimizes the concept design of electrified drive systems, including fuel cell drive systems, with a focus on affordability and a mix of driving performance and low energy usage. While multiple gearbox types were considered, the optimization procedure only looked at one drivetrain topology with a single electric machine. A framework for optimizing FCEVs employing various energy storage systems is provided in [25]. A number of approaches to enhancing the power management strategy were investigated. Furthermore, fuel cells and electric energy storage systems were dimensioned in detail, also taking into account battery aging and lifespan costs. In [26], an approach synthesizing and evaluating drivetrain topologies automatically is presented, supporting developers of hybrid drive systems.

2.4 Energy Management Strategies

As introduced in Chapter 1, fuel cell drive systems are usually hybridized. In hybrid drive systems the energy management strategy (EMS) determines the power deployment from the different installed energy storage systems. EMS can be classified in the two main categories rule-based, which contain deterministic and fuzzy based control strategies, as well as optimization-based, which contain global optimization and real-time optimization approaches. The different approaches come with different advantages, disadvantages as well as other implications on the EMS development process which have been presented in [27, 28]. The common goal is typically to increase the efficiency and performance of the drive system.

The optimization of EMS has become increasingly relevant since the significant rise of hybrid electric vehicles being developed and has also been focused by researches in the field of fuel cell drive systems [29]. The authors of [29] already introduced a real-time capable equivalent consumption minimization strategy (ECMS) for FCEV in 2002. The formulation of the minimization problem proposed in [30] is the following:

$$\sum Min\ \dot{m}_{f_{equ}}(t),\ \forall t \tag{1}$$

with

$$\dot{m}_{f_{equ}} = \dot{m}_{f_{FC}} + f_{pen} * \dot{m}_{f_{REESS}} \tag{2}$$

with the fuel flow into the fuel cell $\dot{m}_{f_{FC}}$ and the equivalent fuel flow of the REESS $\dot{m}_{f_{REESS}}$, estimated by weighing the electrical energy transferred over the boundaries of the REESS with the efficiency of the fuel cell and f_{pen} as penalty factor. The penalty factor is a cubic function depending on the state of charge (SOC) of the REESS – it is more expensive to utilize the battery when the SOC is low in order to reduce the deviation from the desired SOC. A comparable approach is used in this work.

The challenge of integrating the optimization of the EMS in the drive system design process has been approached by researchers in multiple ways. In [31], the parameters for the drive system specification of a plug-in hybrid electric vehicle and the parameters for the fuzzy-based control responsible for power-split and gear shifting have been optimized together in a single loop. The authors of [32] proposed a method focusing on the sizing of ultracapacitors and batteries in FCEVs. Optimizing the utilized EMS was a part of the single-loop optimization problem aimed at reducing initial cost, running cost, and cost associated with degradation. In [33], the EMS was preliminary developed. The drive system design was optimized focusing on efficiency with the EMS being applied to suit the installed component sizes.

Other researches proposed an approach based on two optimization loops. In [34], a hybrid electric propulsion system for ships was optimized utilizing two integrated layers of optimization. The authors of [35] researched the applicability of the different optimization methods GA, sequential quadratic programming, particle swarm optimization and pattern search for the outer loop and dynamic programming for the inner loop when optimizing the drive system (outer loop) and EMS (inner loop) of a hybrid heavy duty vehicle. In [36] two integrated GA loops were used to optimize a hybrid electric drive system and the corresponding EMS.

3 Methods

This chapter introduces the drive system design approach and the different approaches towards the integration of the EMS integration in the design approach considered in this work.

3.1 Design Approach

The authors presented an approach towards the automated design specification of FCEV drive systems in [37]. This approach considers the vehicle class for which the drive system is developed as well as further performance requirements indicated by the expected usage profile and is depicted in Figure 3.

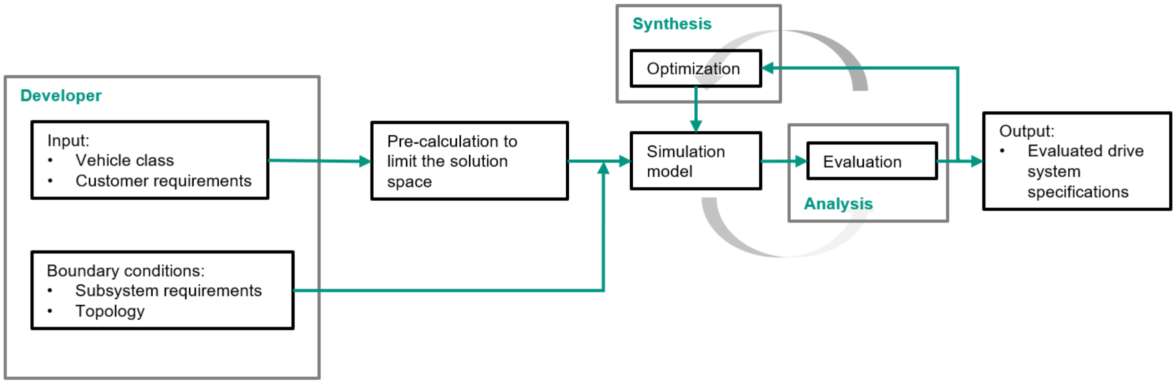

Figure 3: Design approach (schematic) [37]

A multi-objective optimization heuristic based on the NSGA-II is coupled with a scalable techno-economic FCEV model to enable developers to identify Pareto optimal configurations of FCEV drive systems satisfying customer demands. Furthermore, the impact of e.g. modified requirements or changes to the cost of drive system components can be assessed. The evaluation objectives considered during the optimization in this work are the hydrogen consumption of the vehicle (determined by the drive system efficiency in different driving cycles), the acceleration capability of the vehicle, and the drive system cost. [37, 38]

3.2 Integration of the EMS optimization

To integrate the optimization of the EMS into the design method, different approaches were elaborated. The basic optimization of the design parameters without optimizing the EMS is referred to as *A0*. The first integration approach – referred to as *A1* – simply expands the design parameter set optimized with the ECMS parameters. Thus, both parameter sets are optimized simultaneously in a single optimization loop. A flowchart of the approaches *A0* and *A1* is depicted in Figure 4.

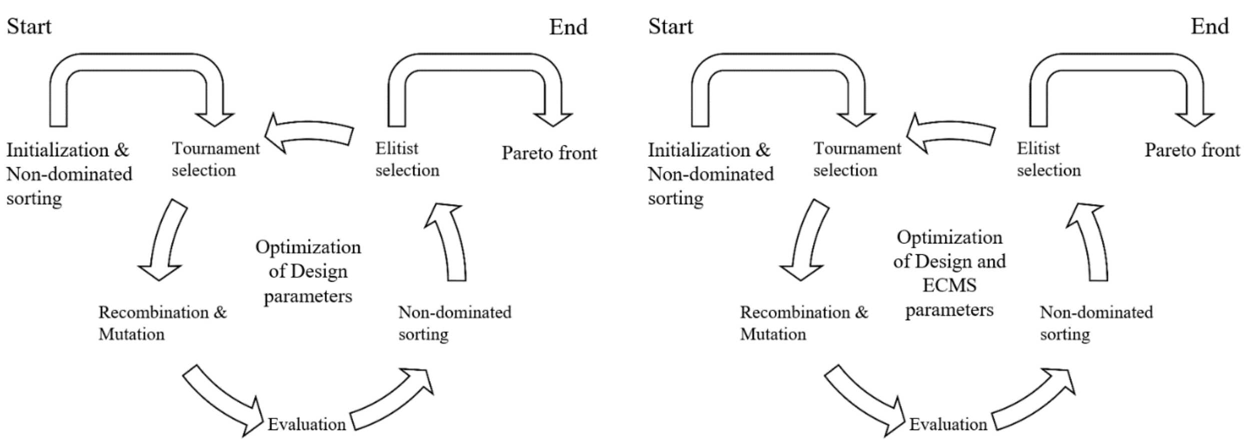

Figure 4: Single-loop optimization approaches A0 (left) and A1 (right)

Another possible way to integrate the EMS optimization is depicted in Figure 5. It consists of two consecutive optimization loops and is referred to as *A2S*. While the design parameters are optimized in the first optimization loop, another optimization loop follows which optimizes the ECMS parameters for each solution that is a part of the design Pareto front. Thus, an ECMS Pareto front will be returned for each solution of the design Pareto front.

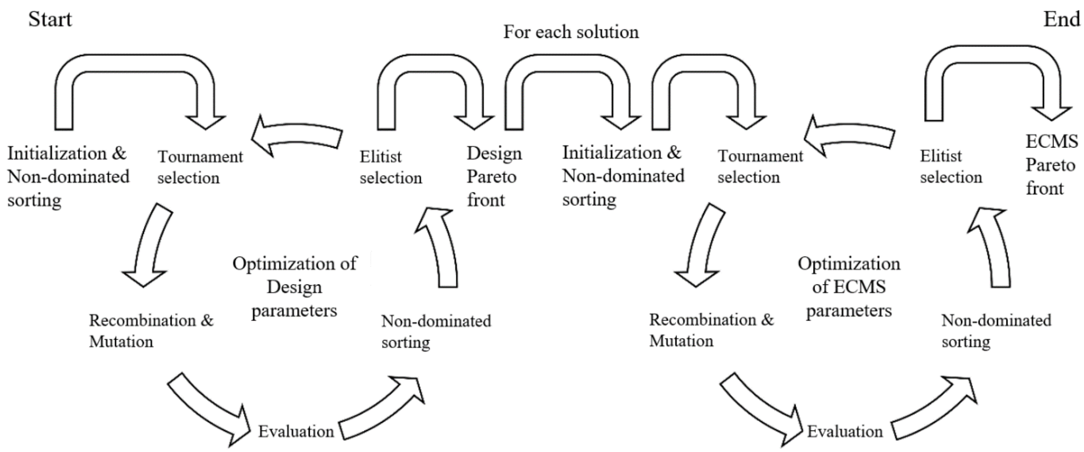

Figure 5: Two-loop approach A2S

The third approach considered in this work consists of two nested loops and is referred to as *A2P*, see Figure 6. The EMS optimization loop is nested in the design optimization loop. For each parameter set in the design optimization loop an ECMS parameter set is optimized before the design parameter set is evaluated. On the contrary to *A2S*, this approach only returns a single Pareto front consisting of solutions with an optimized set of design and ECMS parameters.

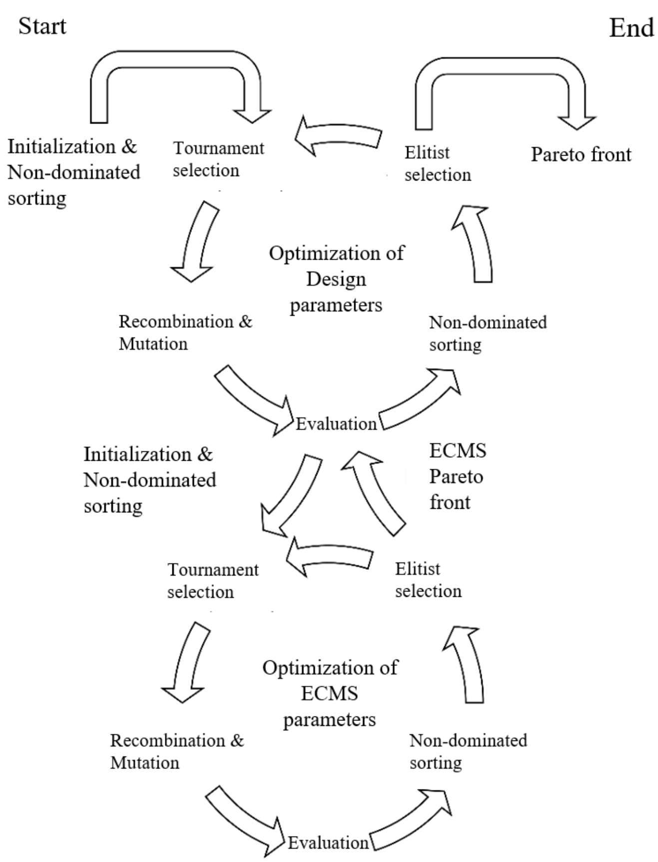

Figure 6: Two-loop approach A2P

The computational time necessary to run the optimization is dependent on the size of the population (P) and the amount of generations (G) of the GA. However, the presented approaches also differ regarding their complexity which also impacts the computation time. The resulting complexities are given in Table 1.

Table 1: Complexity of the different approaches

Approach	Complexity
A0	GP
A1	GP
A2S	GP^2
A2P	$(GP)^2$

4 Evaluation

The presented approaches towards the integrated optimization of drive system design specification and EMS have been run several times in different configurations to determine robustness and provide data for an evaluation. The design parameters considered in the optimization are the drive system topology (amount and positioning of electric traction motors and transmissions), the fuel cell rated power, the number of battery cells and their configuration, the electric traction motor rated power, hydrogen storage capacity as well as the transmission ratio. The ECMS parameters optimized are the parameters defining the cubic penalty factor f_{pen} introduced in Chapter 2.4. The chassis model used to represent the vehicle is an upper-middle class sedan.

The optimizations were run with two different settings for the GA: Either with a population of 250 for 200 generations or with a population of 125 for 400 generations. The development of the hypervolume as well as the amount of non-dominated solutions for the approaches *A0* and *A1* are depicted in Figure 7 and Figure 8.

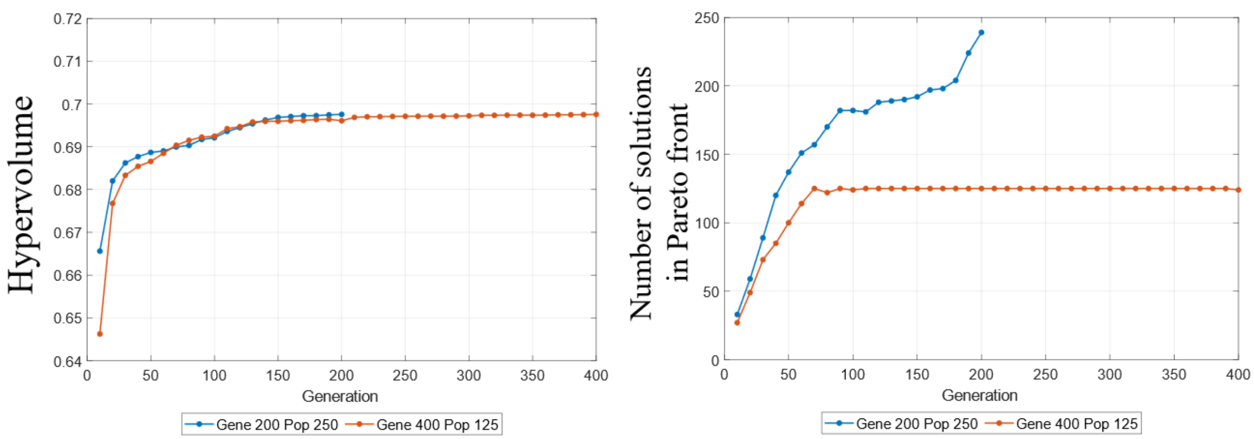

Figure 7: Development of the hypervolume (left) and the amount of solutions in Pareto front (right) – Approach A0

It can be concluded that, in both cases, the optimization seems to converge. While there is only a minor difference regarding the hypervolume it is clear that the setting with a higher population leads to more solutions on the Pareto front. The distribution of the solutions is more even after more generations ran (as has been also confirmed by analysing the crowding distances). The approach with a population count of 250 running for 200 generations is used for further evaluations. The approach *A1* manages to reach same levels of hypervolume and is converging just as quickly as the approach *A0.* No disadvantage could be identified despite increasing the number of parameters that are being optimized. It is concluded that the basic parameter set of the ECMS, that is utilized for all drive systems in the approach *A0,* delivers good results regarding acceleration performance of the vehicle and efficiency.

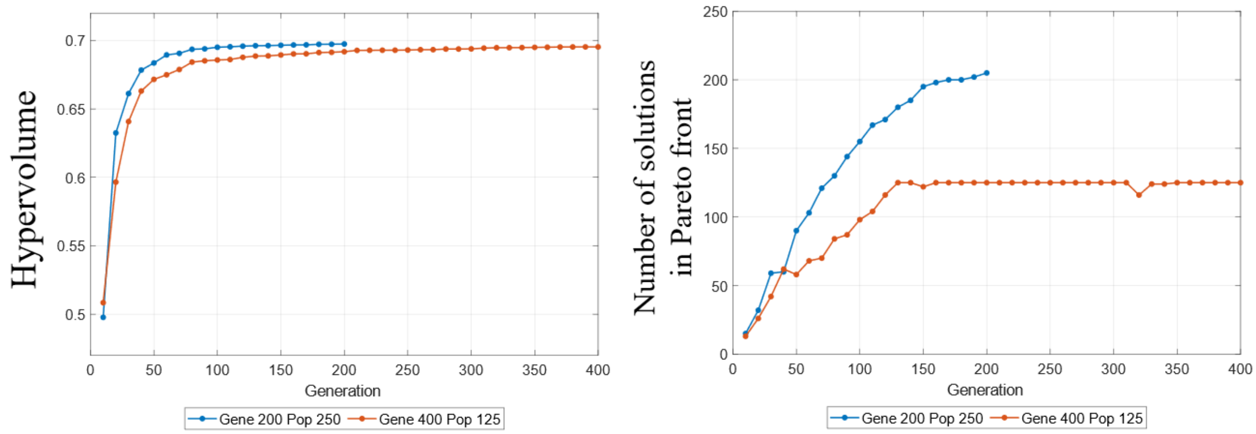

Figure 8: Development of the hypervolume (left) and the amount of solutions in the Pareto front (right) – Approach A1

A comparison between all approaches introduced in Chapter 3.2 has been made. The Pareto fronts are depicted in Figure 9. To enable a visual comparison, only the two objectives acceleration capability and hydrogen consumption (determined by the drive system efficiency) have been considered.

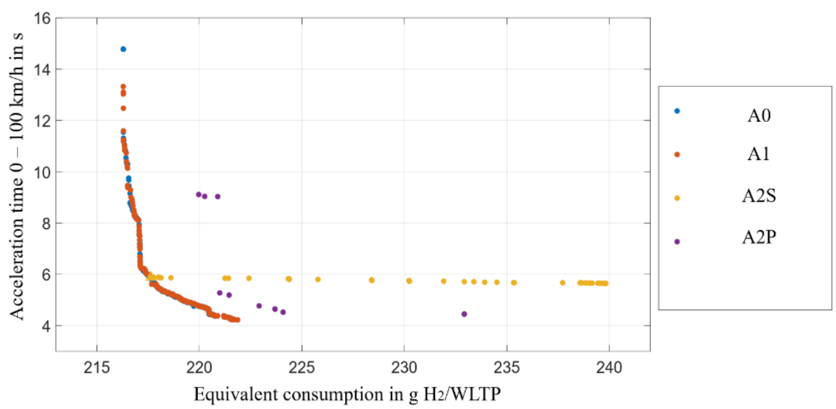

Figure 9: Pareto fronts for the different approaches

For the presented comparison the complexity has been normalized. Thus, *A2P* had a lower population and a reduced number of generations compared to the other approaches. *A2S* was only completed for a single design solution. It can be concluded, that, with a normalized complexity equalling a population of 250 and 200 generations for *A1,* the approaches with two loops are not able to provide results of the same quality as *A1*. *A2P* has not converged yet while the result of *A2S* shows, that, after converging, the *A1* Pareto front already includes the most efficient configuration of the optimized singular vehicle.

To further differentiate the performance of *A0* and *A1,* drive systems were also optimized considering cost and hydrogen consumption. The results (costs normalized, cost model based on [39, 40, 41]) are presented in Figure 10. *A1* performs much better considering the drive system cost. It seems the simultaneous optimization of drive system design and ECMS parameters yields better results. A more thorough check of the single solutions showed much smaller components being used in the *A1*-solutions, resulting in lower costs while still being on par or slightly better regarding acceleration performance and efficiency.

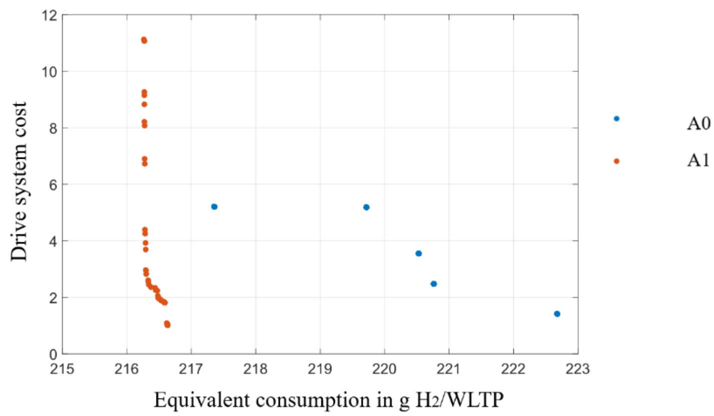

Figure 10: Pareto fronts comparing A0 and A1

5 Summary

In this work, an overview over optimization approaches utilized in drive system design and EMS development for fuel cell and other hybrid drive systems is given. A method for the automated design of fuel cell drive systems is presented. The optimization of the EMS, based on an ECMS, is integrated in this method in three different approaches. These approaches are then evaluated regarding their optimization performance and optimization results. It is concluded that *A1* is the most suitable approach for the present challenge. Due to the lower complexity of this single-loop approach it requires a comparably low computational effort while delivering better results that the optimization of the drive system specification without optimizing the EMS. Therefore, it is evident that the EMS has to be considered in the drive system design process in the presented method. None of the presented approaches with two loops could deliver drive systems with superior performance regarding acceleration, efficiency and costs. The next development steps for the presented approach will be concerned with further decreasing the computational effort and increasing the level-of-detail of the optimization by considering more drive system design parameters and more ECMS parameters. Also, only drive systems for passenger cars have been considered. Thus, the scope will be expanded towards trucks and other commercial vehicles as fuel cell drive system adoption is expected in these vehicles.

Acknowledgments

This paper presents excerpts of the results of the project „Methoden zur arbeitsteiligen, räumlich verteilten Entwicklung von H2-Brennstoffzellen-Fahrzeugen in Kooperation mit China - MorEH2“. The authors are grateful to the German Federal Ministry of Education and Research for funding this project (Funding No.: 16EMO0316).

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