Multi-Objective Optimization of Hybrid Electric Vehicles Considering Fuel Consumption and Dynamic Performance

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***Abstract*—In this paper a new concept for the layout of hybrid-electric-powertrains is developed that includes optimization of the component-sizes as well as control strategies. In contrast to most existing publications, the approach explicitly considers the conflicting goals of low fuel consumption and high vehicle longitudinal dynamics and the trade-off is quantified. Two multiobjective optimization subproblems are solved for one example with a parallelized genetic algorithm (NSGA-II) using the Condor software framework. The analysis of the solutions (Pareto front) shows that combinations exist which improve the fuel consumption with only a slight deterioration of the dynamic performance. So the designers are supported in their decision for a configuration which is attractive for the customers.**

***Index Terms*—simulation, optimization, multi-objective, fuel consumption, dynamics, energy management, hybrid electric vehicle (HEV), component sizing, hybridization, control strategy, genetic algorithm, dymola, modelica**

I. INTRODUCTION

Due to the rising demand of resources worldwide, a changing political environment and social trends, new requirements on the technical development of vehicles arise. Alternative propulsion systems like hybrid vehicles provide more degrees of freedom for the delivery of power, resulting in a fuel-saving potential for example. However, the design of such systems becomes more complicated because of the interaction of the components and the high number of parameters. Therefore, engineers need suitable tools for evaluating drive concepts and control strategies in an early stage of development. Computer based modeling, simulation and optimization is the most appropriate way for dealing with the numerous possibilities.

The following paper describes an optimization concept for the layout of a parallel hybrid electric powertrain that concerns mainly component sizing but also the control strategy. Many previous studies deal with the dimensioning of the drive train components in such vehicles. Most of them concentrate on the objective of minimizing fuel consumption and use constraints for guaranteeing a certain dynamic performance of the vehicle. This is done by putting restrictions on the design variables, e.g. by keeping the power-to-weight ratio [1] or the total vehicle power [2] constant. Or limits on objective values like the passing times 0-60 mph, 40-60 mph, 0-85 mph, etc. are used that are similar to the criteria formulated by the Partnership for a New Generation of Vehicles (PNGV) [3], [4], [7]. In [5] and [6] either fuel consumption or the 0-60 mph time is optimized. The method described in this paper aims on finding the trade-off relationship between the conflicting goals of low fuel consumption and high dynamic performance. This allows the designers to choose from many alternative solutions. Therefore, in contrast to the previous mentioned works, a multi-criterion optimization is done by using a genetic algorithm (GA). This type of algorithm is also used in [8] and [9] but with different objectives like emissions or electrical energy consumption as additional criteria. A further difference of the proposed approach is the use of an object oriented feed-forward dynamic model, built-up in Dymola/Modelica. The advantage is that all energy flows inside of the vehicle can be quantified and fuel consumption as well as acceleration times can be calculated accurately. However, the optimization has to deal with the higher computational effort compared to the models used in [1]-[6] and [8] so that distributed computing is applied here. Further, because of the curse of dimensionality, the optimization problem is splitted in two subproblems: The optimization of the control strategy and the optimization of the component sizes of the drive train.

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II. MODELING

The model used in the work for this paper is a total vehicle simulation in Dymola/Modelica. The tool was chosen because its ability of handling every relevant energy type and flow

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eliminates the need for the use of several different tools. The language Modelica supports object-oriented programming and allows the usage of common model libraries with uniform interfaces to permit element exchangeability. All this leads to high flexibility.

The model consists of submodels for the driver, drive train (engine, transmission and wheels), electrical system, coolant system, exhaust system as well as the air conditioning and heating system. The models exchange their physical values through connectors and communicate via a signal bus system. For example, all relevant heat flows between the subsystems can be considered as well as the cabin heating performance and the temperature depending behaviour of components like the gearbox, the rear-axle transmission or the catalytic converter [10]. The drive train topology considered in this paper is a parallel hybrid electric vehicle (PHEV). The modeled reference vehicle is an upper class car with an 180 kW spark ignition engine. The electrical machine is mounted on the crankshaft through a clutch and is connected by an 8-gear automatic transmission with torque converter to the final drive and the wheel model. This contains wheel-slip calculations and includes an anti wheel-slip device for getting realistic results. The electrical motor model is scalable by changing the nominal torque and is described in [11]. So the power of the motor can be varied during the optimization. The electrical storage consists of Li-Ion batteries and is also connected to the coolant system.

A. *Control Strategy*

Besides the hardware components, building the hybrid drive train, the control strategy (CS) plays an important role in the whole system and influences the overall fuel consumption in a driving cycle. In the case of a PHEV the following modes are available and implemented in the model: Conventional driving by the combustion engine, electrical driving using only the electrical components, conventional driving while recharging the energy store, conventional driving with torque assist by the electrical machine and regenerative braking.

In the presented work a rule-based strategy was applied, that decides which mode is activated dependent on the torque request by the driver, the speed of the crankshaft and the actual state of charge (SOC). The basis of the strategy are considerations on the efficiency of the internal combustion engine (ICE) and the electric machine (EM) like shown in [12]. A characteristic of the CS is that no efficiency tables of the components have to be used. This leads to a generalized structure that ensures an operation which is independant of the hybridization factor [11]. However, it contains parameters that were introduced as decision variables for the optimization process and allow the adaption of the strategy to a specific type of engine for example. For a better understanding, the CS and their variables are described more detailed in Section III.

III. Optimization

In the following subsections the optimization problem is formulated and it is explained, how it is divided into two subproblems in this paper. Afterwards, the used algorithms are described.

A. *Problem Description*

When designing a hybrid drive train, the aim is finding the optimal combination of components and the optimal control strategy for these. Only with a suitable control strategy, fuel-saving potentials can be exhausted. Therefore, the control strategy has to be adapted to the drivetrain when a configuration is evaluated.

In the succession of this paper, decision variables of the hardware, which are considered, are the hybridization factor HF, defined as

$$HF = \frac{P_{EM}}{P_{EM} + P_{ICE}}, \tag{1}$$

the final drive ratio and the battery size, where P_{EM} is the power of the electric machine and P_{ICE} the power of the internal combustion engine. The HF affects the fuel consumption [1]-[3] but it also influences the dynamic performance [3] because of the changing weight of the vehicle and the additional torque, the EM can provide. The determination of the last mentioned trade-off is the central point of this work. Further goals like costs or emissions are imaginable.

For finding trade-offs between the goals, the problem is fomulated as a vectorial optimization. In this case, two or more criteria are compared vectorial. The solution of such a problem is a set of solutions called non-dominated solutions or Pareto optimal set [13]. That means that no feasible solution exists which would decrease a criterion without increasing at least one other criterion. The analysis of the Pareto Front in the objective space lets the designer choose a single solution from all best compromise solutions.

In combination with the decision variables of the control strategy described in the next subsection, the whole problem is visualized in Fig. 1, with the decision variables (left) and the criteria (right). The integration of the electric energy consumption is essential if the CS is not charge sustaining for the different drivetrain hardware.

Because of the high computational effort of the existing detailed car model with about 15 min per simulation run, solving the combined problem is very time-consuming. Therefore, the number of objectives should be limited to 2 in this paper and a stepwise approach is favored. Despite the application of distributed computing, this was necessary because the number of simulation runs needed by the GA for finding a good representation of the Pareto Front rises exponentially with the number of objectives.

The results of this paper (see Section IV) allow the sequential solution in two steps: First, the parameters of the control strategy are optimized with the criteria fuel consumption and electric energy consumption for different HF. The results of these optimizations are a set of CS-parameters that are suitable for different HF and equivalence factors that allow the conversion of electric energy in an equivalent of fuel. So all following optimizations can be performed with a combined

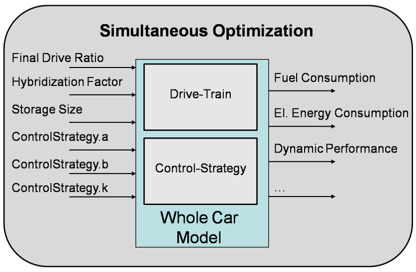

Fig. 1. Simultaneous optimization of the control strategy and the component sizes of the drivetrain

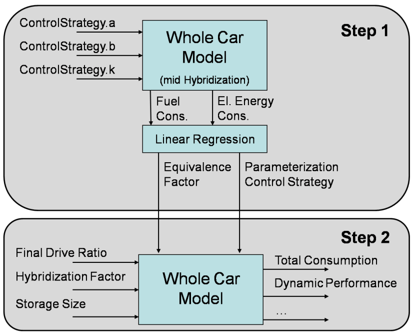

Fig. 2. Stepwise optimization: Step1: Control strategy, Step2: Component sizes

measure for the fuel efficiency (Fig. 2) and one criterion is saved. With the generalized CS it would not be possible to get results with neutral SOC after a driving cycle for different hybridization factors.

1) Control Strategy: The control strategy (CS) of a hybrid vehicle decides on the interaction of the drive train components. Therefore, the CS and the HF affect each other and the fuel economy. In the implemented strategy, electrical driving is chosen whenever possible, that means depending on the required power and the available SOC. Furthermore, the ICE is switched off when it is not required. When the ICE is switched on, the CS decides, if a load-point shift is usefull or not and determines the amount of the (negative) torque, the electric machine (EM) applies to the crankshaft for charging the batteries.

According to [12], a load-point shift is only useful for points with small loads. Therefore, switching points can be characterized by the proportion of the engine torque needed for propulsion T_{ICE} and the engine speed n_{ICE}. As a result, a state-of-charge-based characteristic curve of decision can be used that is explained in [11]. The CS had been manually tuned for good fuel economy for one combination of drive train components. This manual tuning does not guarantee best parametrization of the strategy. Therefore it is desirable that besides component sizing also the control strategy can be optimized. For that, three decision variables were added to the strategy of [11] for allowing a tuning of the CS by the optimization proceess. So, the decision for recharge is:

$$CS.b\frac{T_{ICE}}{n_{ICE}} < -0.5\tanh(CS.a(SOC*4-2)+0.5) \quad (2)$$

TABLE I
OPTIMIZATION PROBLEM OF THE CONTROL STRATEGY

	Variables			Criteria	
Meaning	Decision Recharge	Power Recharge	Transition Recharge	Fuel Cons.	SOC End
Symbol	$CS.b$	$CS.k$	$CS.a$	f_c	$-SOC_{end}$

TABLE II
OPTIMIZATION PROBLEM OF THE COMPONENT SIZING

	Variables			Criteria	
Meaning	Hybr. Factor	Number Batteries	Ratio FD	Fuel Cons.	Time 0-150 km/h
Symbol	HF	n_{bat}	i_{fd}	f_c	t_{acc}

$CS.a$ changes the SOC-dependent adjustion of the curve for prohibiting a depletion or an overload of the batteries and so the SOC stays between defined limits SOC_{low} and SOC_{high}. $CS.b$ influences the basic gradient of the curve so that the CS can be adapted to the efficiency of the components. The third variable $CS.k$ determines the setpoint for the motor torque used for recharging by the EM $T_{EM,set}$ by a percentage of the maximal possible torque $T_{ICE,max}$ and the torque required for propulsion T_{prop}:

$$T_{EM,set} = max[(-T_{EM,max}, T_{prop} - CS.k*T_{ICE,max})] \quad (3)$$

When measuring the fuel economy of an HEV, the deviation of the SOC at the end of a drive cycle SOC_{end} and the SOC at the start SOC_{start} has to be taken into account, as it represents an electrical energy use or gain. Here, it is influenced by all three variables. The following investigations and all optimizations were carried out with the european Motor Vehicle Emissions Group (MVEG) drive cycle and with $SOC_{start} = 80\%$. As objectives, the fuel consumption f_c in the MVEG cycle was minimized and SOC_{end} as a measure for electric energy consumption was maximized for getting best efficiency. Because the algorithm minimizes all criteria, formally $-SOC_{end}$ was used. Table I summarizes the optimization problem of the Control Strategy.

2) Component Sizing: For the optimization, measures of the criteria have to be defined. For determination of the fuel consumption f_c, again the MVEG cycle was simulated.

Measuring dynamic performance is imaginable in different ways. Because of the high computational effort of a single simulation run, a simple measure, namely the acceleration time 0-150 km/h using full trottle and the maximal electric torque assist t_{acc} was chosen as single performance criterion.

The decision variables of the optimization problem were the HF (1) of the drive train, the number of batterie cells n_{bat} and the final drive ratio i_{fd}. The HF was varied by changing P_{EM} using the scalable motor model. In contrast to [3], the total power of the system is not kept constant, because the engine is not scaled here. Table II shows the formulated problem of the component sizing.

B. Algorithm

Solving a multiobjective optimization problem corresponds to searching for the Pareto optimal set. Multiobjective Genetic Algorithms (MOGA) are suitable for such problems because they work with a set of solutions, called individuals of a generation. The result of one optimization run is an approximation of the Pareto front [13]. In this approach, the criteria are not aggregated to a weighted sum and the real trade-off can be found. Another strength of GAs ist that they can cope with discontinuities of the objective functions and are global optimizers. That means the danger of getting stuck in local minima is lower than with techniques that work with gradients. So they are well suited for problems with unknown relationship between the decision variables and the objective function values, also called optimization with "black box"-functions.

So the widespread nondominated sorting Genetic Algorithm II (NSGA-II) was chosen in this paper. Its working principle is not explained here, it can be found in [14]. When optimizing with "black box"-functions, one simulation run has to be executed for each evaluation of an objective function vector. So for getting a viable approximation of the Pareto front, a high number of simulations per generation as well as multiple generations have to be calculated. Using the Dymola model, one single simulation run takes 15-20 min on a state of the art desktop PC, which doesn't allow a solution of the problem in an acceptable time. Fortunately GAs are well suited for distributed computing, because each fitness function evaluation of the individuals of a generation can be performed simultaneously. In [16] this approach is called "master-slave"-model. The result is exactly the same as that with a single processor, but the computational time is lower.Thus the code of the original algorithm was changed so that the simulations of one generation are performed in parallel. For distributing each simulation of a generation on one processor, the Condor software framework was used [17]. Condor is developed at the University of Wisconsin since the mid 1980s and is suited most for enclosed computer networks without firewalls. It also combines well with the Dymola simulation environment as Dymola compiles the simulation into a standalone running executable so that Dymola itself does not have to be installed on the single nodes of the grid. In average, 30 computers of an university computer pool were available. As condor was not designed to have the submit node (here the GA) to sit outside a firewall as in this case, a MATLAB Application Programming Interface (API) was implemented allowing the GA to access the grid via SSH. The process and the communication of the software packages is visualized in Fig. 3.

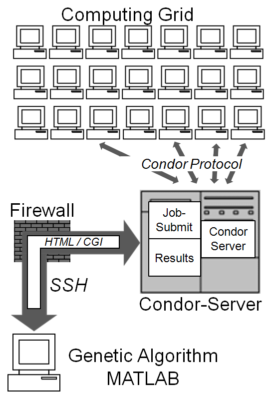

Fig. 3. Cooperation of the software in the optimization process

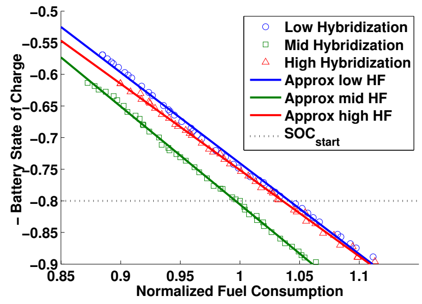

Fig. 4. Results of the optimization with three different hybridization factors and 50 batterie cells

IV. Optimization Results

According to the problem description in Section III, at first an optimization of the control strategy was carried out. The gained parameter values were then used during the optimization of the component sizes.

A. Optimization of the Control Strategy

Fig. 4 shows the result of the optimizations of the CS for three different hybridization factors HF_{low}, HF_{mid} and HF_{high}. Also the regression lines for each HF are shown. It can be seen that the relationship between the fuel consumption and SOC_{end} can be approximated by linear functions. This coincides with results shown by [15] but the straight line is determined in a different process as in the cited paper. Also in [9] a linear behaviour can be observed. It can be explained with averaging effects of the load points in the MVEG cycle.

So the slopes of these functions can be used for the calculation of equivalence factors for converting changes of the state of charge $\Delta SOC = SOC_{start} - SOC_{end}$ in equivalent fuel consumptions. These deviations represent an electric energy consumption and have to be taken into account when judging the efficiency of the system. They will occur when the HF is varied and the control strategy is not adapted to the combination of drive train components. The results also reflect the known effect that the fuel consumption decreases until a certain hybridization factor and then increases for high hybridizations [1],[11].

B. Optimization of the Component Sizing

For the following optimization of the component sizes, the variables which lead to no SOC deviation ($SOC_{end} = 80\%$) for the mid hybridization were selected. The limits of the decision variable space are listed in Table III.

Fig. 5 shows the first front after 20 generations with 70 indiviuals. The results are normalized with the results of the non-hybrid car. Fig. 6 - Fig. 8 depict the correspondent projections of the variable space. In the front of the best individuals there exist areas, where a better fuel consumption can be achieved with a relative low deterioration of the acceleration time. The selected solution marked with a triangle represents a good compromise of fuel consumption and performance and has an HF of 0.28. Lower consumptions would have to be paid with a relative bigger increase of the acceleration time. One example of a bad trade-off (marked with a square) with an hybridization of 0.26 shows an decrease of fuel consumption of only 0.2% but an increase of t_{acc} of 3.1%. The configuration with the lowest fuel consumption is part of the solution of the optimization process. It can be found on the left end on the front in Fig. 5 and is marked with a star. Its HF is 0.21. Compared to the selected solution, its consumption is improved by 3.4% and the acceleration worsened by 9.8%.

In all combinations, the suitable final drive ratio is between 3 and 3.5 (Fig. 7, Fig. 8) and the influence of this variable on the two goals is rather low. Additionaly, the examination of the variable space shows that the number of battery lies allways near the defined lower limit of 90 cells of 45 Ah at 3.6 V in this example (Fig. 6). This limit was chosen here, for guaranteeing a minimum all electric range (AER) and this battery pack is big enough for the hybrid functions in the MVEG cycle. This is documented in the simulation results in Fig. 9 which show the vehicle speed, the SOC, the normalized fuel consumption and the electric torque in the MVEG cycle for the compromise solution. It has to be noted that the fuel consumption is the value without correction with the ΔSOC. In this case, it is $SOC_{end} = 78.8\%$. The nominal torque of the EM is not used often for propulsion but especially in the recuperation phase at the end of the cycle. P_{EM} of course influences the acceleration time (Fig. 10). Compared to the conventional car, the HEV has clear advantages over 45 km/h, at lower speeds wheel-slip effects dominate.

First optimizations with different limits for the electric storage size or with different storage technology have shown that the process determines reasonable combinations of hybridizations and storage sizes for both the best consumption and the compromise solutions. The results of these are not shown here.

V. Conclusions and Future Works

The results show that the multicriterion optimization of the component sizes concerning fuel consumption and dynamic

TABLE III
LIMITS OF THE DECISION VARIABLE SPACE

Variable	Range	Selected Solution	Best Cons.
Hybridization Factor	0.14 - 0.34	0.28	0.21
Number Batterie Cells	90 - 120	91	90
Final Drive Ratio	3.0 - 4.5	3.3	3.3

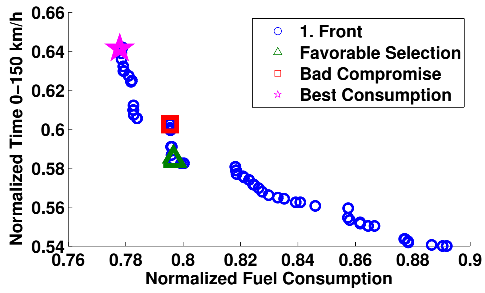

Fig. 5. Objective space after optimization of the component sizes, normalized on the conventional car

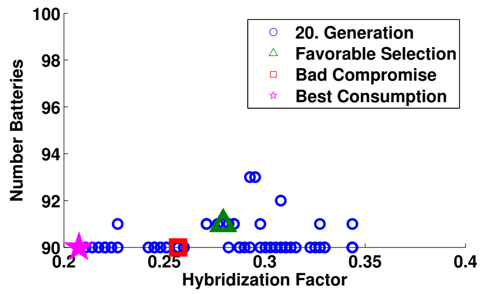

Fig. 6. Projection of the variable space: Hybridization Factor vs. number of batterie cells

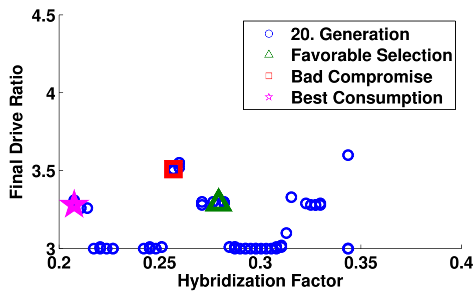

Fig. 7. Projection of the variable space: Hybridization Factor vs. final drive ratio

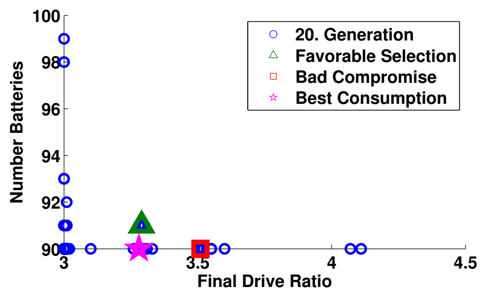

Fig. 8. Projection of the variable space: Final drive ratio vs. number of batterie cells

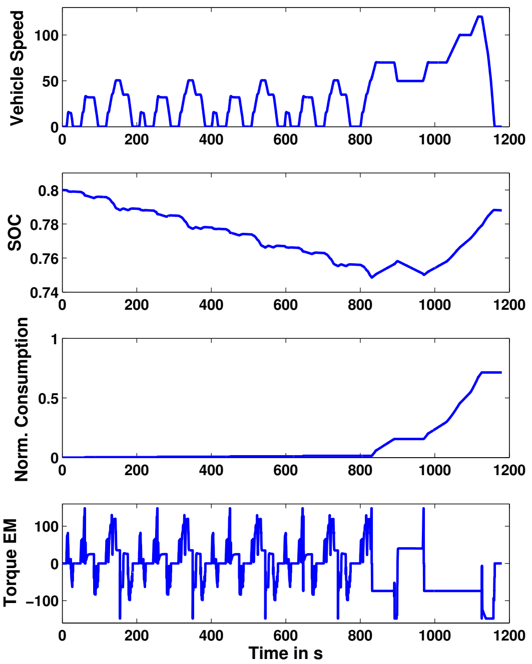

Fig. 9. Simulation results of the MVEG cylce of the selected compromise solution

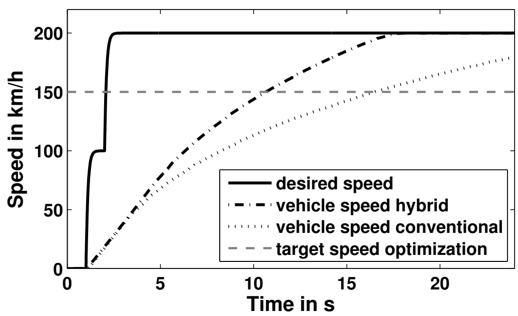

Fig. 10. Comparison of the simulated acceleration of the selected compromise solution and the non hybrid car

perfomance is a meaningfull addition to other optimizations during the layout of parallel hybrid drive trains. The generalized CS makes the different drive-train hardware comparable. However, it does not claim to find the global minimum of fuel consumption for the single solutions which can only be determined separately for every combination with a priori knowledge of the driven cycle. Additionally, for practical implementations, more values like exhaust temperatures have to be taken into account.

The resulting set of compromise solutions, gives the designers important hints for choosing suitable combinations of drive train components for further investigations. The presented example shows that starting from a certain hybridization with lowest possible fuel consumption, increasing P_{EM} brings better dynamic performance with only sligthly increasing consumption. With even higher hybridizations, the improvements of the performance are getting lower but the fuel consumption grows faster. Variation of the final drive ratio has a lower impact, only the fastest solutions show the biggest ratios but are combined with the worst consumptions.

In future works, hybrid vehicles with smaller combustion engines will be considered as well as different drive-train topologies and energy storages. Additionally, the engine power will also be scaled, so that the effect of down-sizing concepts can be evaluated.

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