

Multi-Objective Optimal Design of Parallel Plug-In Hybrid Powertrain Configurations with Respect to Fuel Consumption and Driving Performance

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ABSTRACT

In the past decade, various Plug-in Hybrid Electric Vehicles have been demonstrated which offer the potential of a significant reduction in fuel consumption and emission. However, this capability strongly depends on the sizing of the components, driver's usage profile and the quality of the energy management. These challenges require new optimization procedures for a systematical exploration of the design space with the objective of an optimal powertrain configuration. A novel optimization strategy based on a multi-objective problem formulation is proposed. The optimization procedure consists of a multi-objective genetic algorithm for determining the best design parameters with respect to fuel consumption and driving performance. The approach is combined with an analytical optimal control problem to find the optimal continuous and discrete control trajectories for the energy management.

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INTRODUCTION

Both - fuel consumption and emission in the field of transportation can be reduced remarkably by electrified powertrains and become a more and more important topic for the automotive industry. Therefore, Plug-in Hybrid Electric Vehicles (PHEVs) have been considered as a linking technology from Hybrid Electric Vehicles (HEVs) towards Battery Electric Vehicles (BEVs). PHEVs offer all the merits of sustaining HEVs, e.g. downsizing, regenerative braking, etc., with the additional feature of storing (green) energy from the electrical grid using batteries with high-energy densities [1].

On the other hand, hybrid powertrains introduce a multitude of components and design parameters which have to be properly sized and controlled so that the entire powertrain ensemble achieves its optimal efficiency. It is therefore important to study the size effects of the critical components like electrical machine, battery and transmission to obtain an optimal hybrid powertrain configuration of a selected powertrain configuration. For this reason, different global optimization techniques have been applied to find the most efficient powertrain component sizings. For instance, in [2], [3], a genetic algorithm (GA) has been used to find the suboptimal gear ratios, battery capacity,

and electrical machine power with respect to fuel consumption only. In [4], a dynamic programming approach is applied due to the capability to use nonlinear, non-convex models, and mixed-integer optimization variables, whereas a convex optimization scheme for component sizing is proposed in [5] and [6]. In addition to the mainly employed fuel consumption criterion, the battery state of health (SOH) has been considered in [5] for the design process of a hybrid bus.

It is well known in the engineering community that powertrain optimizations with respect to fuel consumptions only yield sub-optimal solutions. Some other aspects have also to be regarded:

- Optimizations with respect to fuel consumption result in gear sizing with long gear ratios which are beneficial for low fuel consumption but lead to poor drive performance, i.e. long acceleration times.
- A critical issue in the powertrain design is the interdependence of the component sizing with the control strategy/energy management applied. This aspect makes the problem of sizing even more complex.

The first challenge is addressed by additionally using a subjective drivability performance index (SDPI) which represents the drive performance of the vehicle assessed by different drivers. This inevitably leads to a multi-objective optimization problem.

The energy management problem for HEVs or PHEVs whose main task is to determine trajectories of the torque-split between motor/generator and combustion engine as well as the start/stop sequence has been addressed by many researchers considering dynamic programming [7], Equivalent-Consumption-Minimization-Strategies (ECMS) [8], [9], [10], model predictive control (MPC) [11], and analytical approaches like optimal control theory (OCP). The second challenge is in this case solved by considering the energy management problem for each design trial as a Hybrid OCP (HOCP) subject to continuous and discrete controls [12].

This paper presents the novelty of combining a multi-objective genetic algorithm with a convexified HOCP in order to find the optimal powertrain sizings fast and robustly. This is numerically achieved by embedding the binary switchings of the combustion engine (on/off) and the discrete gear choices (integer values) into a larger class of continuous optimal control problems. By accurately solving this problem, the convexified on/off decisions for the combustion engine become at almost every time instant an integer feasible solution, whereas the continuous trajectory of a CVT-like modeled gear ratio is discretized by using the optimized gear sets from the non-dominated sorting genetic algorithm II (NSGA-II). This enables with no a-priori knowledge of the switching structure to find the number of switchings, the switching time, and the mode sequence.

This approach expands the work in the previously presented SAE papers [2], [3] with the focus on applying the developed optimization strategy on the optimal gear-ratio and electrical machine sizing for a parallel PHEV. The methodology is explained in detail and some practical considerations are given to avoid unrealistic powertrain designs. The last part of the paper discusses some additional multi-objective problem formulations for PHEV control.

DESCRIPTION OF THE PARALLEL HYBRID VEHICLE MODEL

Various automotive manufacturers investigate the parallel hybrid configuration due to their simple architecture and the ability to apply mass-produced components from conventional vehicles. The electric motor/generator (MG) can be simply integrated in the conventional powertrain using a clutch. The architecture of the powertrain (P2) considered in this paper is shown in Figure 1. It shows a front-wheel driven powertrain with a torque coupling of the thermal path and the electrical path, a clutch to decouple the internal combustion engine (ICE) from the drive train and a differential. The torque coupling is achieved with a dry seven-speed dual-clutch transmission. The

MG is installed between clutch and transmission. Thus, pure electric driving and regenerative braking is possible without the drag-torque of the ICE. In hybrid drive mode (engine on), the ICE and the MG provide together the torque required by the driver. Table 1 summarizes some important vehicle characteristics.

Table 1. Nominal vehicle characteristics

Vehicle class	Midsize Sedan
Weight	1520 [kg]
A* <i>c_w</i>	0.514 [m ²]
Hybrid Configuration	P2 type
Transmission Type	dry seven-speed dual-clutch transmission
MG (motor/generator)	20/(-28) [kW]

Longitudinal Vehicle Dynamics

The design procedure requires a simple longitudinal vehicle dynamics model to provide the road load. Therefore, the friction force at the speed $v(t)$ is calculated as

$$F_{fc} = F_{drag} + F_R + m_{veh}(1 + \lambda_{cf}) \cdot g \cdot \sin \chi \quad (1)$$

where the contribution due to drag F_{drag} and rolling resistance F_R is best approximated by a polynomial of second degree of the vehicle speed, where $v(t)$ is the vehicle speed, $\chi(t)$ is the road inclination, m_{veh} is the vehicle mass, λ_{cf} is the mass correction and g is the acceleration due to gravity. The road load acts on the powertrain through the final drive i_{FD} and the transmission. The simple longitudinal vehicle dynamics can then be calculated using the aggregated vehicle inertia J_{veh} as

$$T_R(t) = r_{wh} \cdot F_{fc}(t) \quad (2)$$

$$T_{wh}(t) = J_{veh} \cdot \dot{\omega}_{wh}(t) + T_{rl}(t) + T_{brk}(t) \quad (3)$$

$$\omega_{wh}(t) = \frac{v(t)}{r_{wh}} \quad (4)$$

where T_{rl} is the road load, T_{wh} is the wheel torque, r_{wh} is the radius of the wheels, ω_{wh} is the angular wheel speed, and T_{brk} is the friction brake torque of the redundant hydraulic friction braking system. The friction brake torque handles the

remaining brake torque if the MG is either limited by its torque limit or by reaching the charging limit of the battery. The vehicle speed trajectory $v(t)$ is given by known drive cycles.

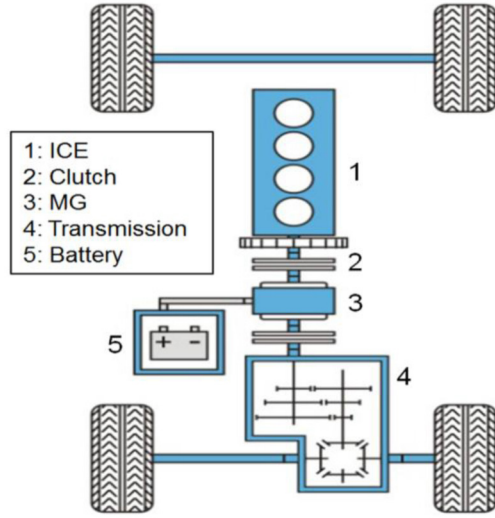


Figure 1. Parallel hybrid vehicle configuration

Modeling of the Powertrain

Modeling of the powertrain and its components is a crucial step for the optimization procedure. The models have to be accurate with regard to the optimization goal but the complexity should be kept moderate to allow many optimization evaluations. Special care has to be taken by the model properties: convexity and smoothness influence the convergence of gradient-based optimization procedures dramatically. This important topic will be treated later in the component sizing paragraph.

The active drive modes at given time t will be denoted by the binary variable

$$\zeta(t) = \begin{cases} 0, & \text{electric drive mode} \\ 1, & \text{hybrid drive mode.} \end{cases} \quad (5)$$

The vehicle has an automatic gearbox with seven gears, whose gear-numbers are included in the set $K = \{1, 2, \dots, 7\}$. The active gear at time t is given by the discrete function $\kappa(t) \in K$. The input torque of the gearbox, T_{clth} , is obtained as follows:

$$T_{clth}(t) = \frac{T_{wh}(t)}{i_{gbx}(\kappa(t))} + T_{loss}(i_{gbx}(\kappa), T_{wh}(t), n_{wh}(t)) \quad (6)$$

with the wheel speed n_{wh} , the discrete gearbox ratio i_{gbx} , and the powertrain friction losses T_{loss} . For the corresponding speed $n_{clth} = n_{wh} \cdot i_{gbx}$ applies. The clutch torque T_{clth} needs to be supplied in sum by ICE and MG at any time:

$$T_{clth}(t) = T_{ice}(t) + T_{mg}(t) \quad (7)$$

where T_{mg} and T_{ice} are the torques of the MG and ICE, respectively.

Within its limits, the torque-split between ICE and MG is variable. Hence, the control $T_{ice}(t)$ is defined as

$$T_{ice}(t) = \begin{cases} 0, & \zeta(t) = 0 \\ T_{ice}(t), & \zeta(t) = 1. \end{cases} \quad (8)$$

The corresponding speeds are

$$n_{mg}(t) = n_{clth}(t)$$

$$n_{ice}(t) = \begin{cases} 0, & \zeta(t) = 0 \\ n_{clth}(t), & \zeta(t) = 1 \end{cases} \quad (9)$$

where n_{mg} and n_{ice} are the speeds of the MG and ICE, respectively.

Lithium ion batteries can be uniformly modeled using a simple zeroth order battery model consisting of an ideal voltage source V_{OC} and an internal resistance R_{bat} . The open circuit voltage (OCV) of the ideal voltage source only depends on the state of charge (SoC) of the battery and is determined from a map. Considering the power losses caused by the battery's internal resistance R_{bat} and applying Kirchhoff's circuit law, one obtains the battery power P_{bat} related to the battery current I_{bat} through the following power balance equation

$$V_{OC} \cdot I_{bat} + R_{bat} \cdot I_{bat}^2 = P_{bat}, \quad (10)$$

Where P_{bat} is the sum of the electrical power of the electrical motor/generator P_{mg} and the power required to supply the electrical on board system P_{on} . Thus,

$$P_{bat} = -(P_{on} + P_{mg}) \quad (11)$$

where P_{mg} is a smooth function of T_{mg} and n_{mg} . The sign of the battery power indicates: battery discharges for $P_{bat} < 0$ and battery charges for $P_{bat} > 0$. Solving Eq. (10) for the battery current I_{bat} yields

$$I_{bat} = \frac{-V_{OC}(SoC) + \sqrt{V_{OC}^2(SoC) + 4R_{bat} \cdot P_{bat}}}{2R_{bat}}. \quad (12)$$

The system's state equation can then be written using Eq. (12) as

$$\dot{SoC} = \frac{100}{Q_{bat}} \cdot I_{bat}(SoC(t), T_{mg}(t), n_{mg}(t)) \quad (13)$$

where Q_{bat} is the maximum battery capacity.

The accumulated fuel consumption of the ICE can be calculated by the differential equation

$$\dot{\beta} = \gamma \cdot \zeta \cdot CF_{fc}(\vartheta_{cw}) \cdot bsfc(T_{ice}, n_{ice}) \cdot T_{ice} \cdot n_{ice} \quad (14)$$

$$\beta(t_0) = 0, \quad (15)$$

where $bsfc$ is the brake specific fuel consumption, ϑ_{cw} is the temperature of the coolant water, and γ is a product of natural constant, such that $\beta(t_i)$ is the total fuel consumed in liters. If $\zeta(t) = 0$ applies, then the fuel consumption is zero.

To take warm-up losses into account, a warm-up correction factor $CF_{fc}(\vartheta_{cw})$ has been determined by the similarity principle using the following relationship

$$CF_{fc} = \frac{\dot{\beta}}{\dot{\beta}_{90}} \sim \frac{90^\circ C}{\alpha(\vartheta_{cw}) \cdot \vartheta_{cw}} \quad (16)$$

where $\dot{\beta}_{90}$ is the fuel rate at warm engine operation ($90^\circ C$) and $\alpha(\vartheta_{cw})$ is a correction factor. The current temperature of the coolant water can be easily approximated by a non-linear first-order differential equation of the form

$$\frac{d\vartheta_{cw}}{dt} = \frac{1}{\tau} (-\vartheta_{cw}(t) + C \cdot (90^\circ C - \vartheta_{cw}(t))) \quad (17)$$

where the coefficient for the heating phase is the ratio of the current to the maximum power of the ICE

$$C = \frac{P_{ice}(t)}{4 \cdot P_{ice_{max}}}$$

and for the cooling phase a constant factor of

$$C = -\frac{1}{800}$$

is used. Figure 2 illustrates the heating phase for the MVEG drive cycle. The temperature increases depending on the produced ICE output power $P_{ice} > 0$ and decreases in electrical drive or stop phases. All necessary data are obtained from measurements collected from ICE test-rigs.

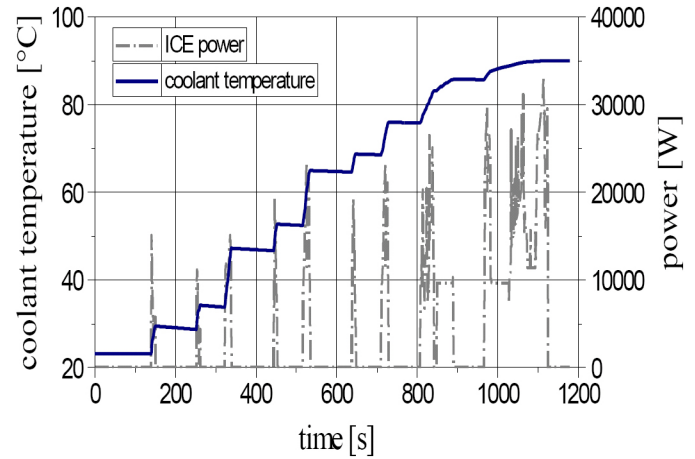


Figure 2. Heat-up process of the ICE in the MVEG cycle

The gear ratios of an automatic transmission define the clutch speed to vehicle speed ratio depending on the wheel radius and the final drive ratio. In order to achieve the optimal fuel consumption, two different design variants for a dry seven-speed dual-clutch transmission were investigated. The first variant is the fully progressive design of the gear ratios with the following definition

$$i_{gbx}^j := i_{gbx}^{min} \cdot \varphi_1^{(n_{gbx}-j)} \cdot p^{0.5 \cdot (n_{gbx}-j) \cdot (n_{gbx}-j-1)}, \quad j = 2, \dots, n_{gbx} \quad (18)$$

where

$$\varphi_1 = \sqrt{\frac{\varphi_s}{p^{0.5 \cdot (n_{gbx}-1) \cdot (n_{gbx}-2)}}} \quad (19)$$

is the basic gear step, i_{gbx}^j is the discrete gear ratio of gear j , φ_s is the total gear spread, p is the progressiveness and n_{gbx} is the number of gears. The highest gear ratio is determined by fulfillment of the creep velocity v_{creep} which should be less than 7 [km/h] as

$$i_{gbx}^1 \geq \frac{3.6 \cdot n_{clth} \cdot 2 \cdot \pi \cdot r_{wh}}{60 \cdot v_{creep} \cdot i_{FD}} \quad (20)$$

whereas the minimum transmission ratio

$$i_{gbx}^{min} := \frac{i_{gbx}^1}{\varphi_s} \quad (21)$$

depends on the desired maximum vehicle velocity, the road load and the provided system power. The second variant considers that all of the gear steps can be chosen individually within certain limits according to the definition

$$\varphi_j := \frac{i_{gbx}^{j-1}}{i_{gbx}^j}, \quad j = 2, \dots, n_{gbx}. \quad (22)$$

Therefore, one can choose either the transmission optimization vector

$$x_{gbx} = [\varphi_s \quad p]^T \quad (23)$$

or

$$x_{gbx} = [\varphi_1 \quad \varphi_2 \quad \varphi_3 \quad \varphi_4 \quad \varphi_5 \quad \varphi_6]^T. \quad (24)$$

In order to keep the gear design of the transmission realistic, the ratio spread and the progressiveness are constrained to

$$\varphi_{min} \leq \varphi_s \leq \varphi_{max} \quad (25)$$

and

$$1 \leq p \leq p_{max}. \quad (26)$$

For the second design variant the change of each gear ratio in Eq. (22) is additionally constrained to

$$1 \leq \varphi_j \leq \varphi_j^{max}. \quad (27)$$

Only permanent magnet synchronous motors (PMSM) have been used for the powertrain design due to the major benefits of high efficiency and well controllability, which make them highly attractive candidates for applications in (P)HEVs [13]. Depending on the considered drive cycle the motor/generator has to be properly scaled to obtain the best efficiency/weight compromise. Therefore, the maximum power and the ratio of base speed over maximum speed are used as design variables

$$x_{mg} = [P_{mg}^{max} \quad b_{mg}]^T \quad (28)$$

where

$$b_{mg} = \frac{\omega_{mg}^{base}}{\omega_{mg}^{max}}. \quad (29)$$

When the speed of the MG increases, then the voltage applied to the motor must increase accordingly to counteract the speed-proportional induced back electromagnetic force in the stator windings. When the speed reaches the rated voltage, the voltage applied to the PMSM cannot be further increased to maintain the stator current for torque production. This speed

is called the base speed ω_{mg}^{base} and plays an important role in designing the MG properly. It is assumed that the ratio of base speed over maximum speed ω_{mg}^{max} for PMSMs lies in a region

$$0.2 \leq b_{mg} \leq 0.6 \quad (30)$$

which is admissible. This assumption has been experimentally validated by an analysis of a series of PMSMs. If the admissible ratio is violated after the scaling procedure, then the machine limits must be adapted. For instance, if the ratio b_{mg} is too high then decreasing the maximum power or increasing the maximum torque of the MG reduces the ratio which can be easily observed from equation

$$b_{mg} = \frac{P_{mg}^{max}}{T_{mg}^{max} \cdot \omega_{mg}^{max}}. \quad (31)$$

If the ratio is lower than the admissible one, then the contrary actions apply.

OPTIMIZATION STRATEGY

An evolutionary algorithm (EA), in form of a genetic algorithm, is often applied in numerical optimization practice to find the best powertrain design parameters including the parameters of the energy management [3]. This is mainly motivated by the fact that EAs can cope naturally with multi-objective, discontinuous and non-differentiable problems, e.g. determining the discrete gear ratios.

Numerical optimizations using efficiencies can result in unrealistic gear selections and shiftings. Extension of the cost function, e.g. with driving performance, can be used to improve the results. However, such strategies lead to multi-objective optimizations which are, in general, more difficult to solve. Since EAs work with a population of solutions. It is therefore a straightforward procedure to extend the simple EA paradigm to maintain and manipulate a diverse set of solutions which finally converge to a set of solutions which cannot be dominated by any other solution. These solutions are known as Pareto-optimal solutions [14]. Another popular approach is to transcribe the multi-objective problem into a single-objective problem by focusing on one particular Pareto-optimal solution at a time. Such methods have the difficulty that this procedure has to be applied many times, hopefully finding different solutions which approximate the true Pareto-optimal front as well as possible. The quality of representing the true or a good approximation of the Pareto-optimal solutions depends on the implementation used.

EAs-based powertrain designs are usually implemented to solve static optimization problems, where the design parameters, including the parameterized energy management, are the optimization variables only. An alternative approach is to solve the underlying control problem as HOCPP. Such

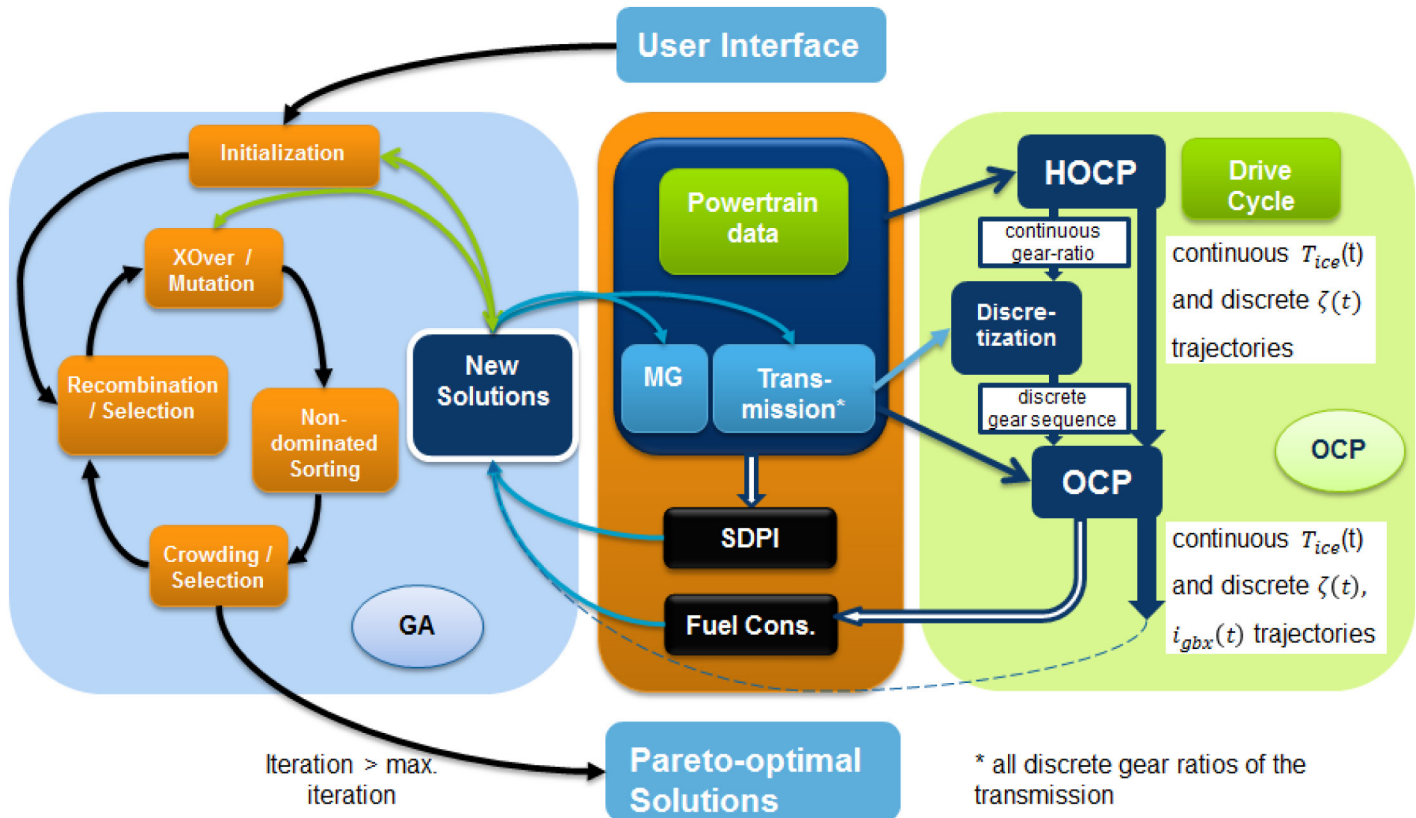


Figure 3. Interaction of the multi-objective genetic algorithm (left) with the optimal control problem solutions (right)

problem definitions can be transcribed into static optimization problems but introduce a number of optimization variables which depend on the discretization of the drive cycle. These methods result in more accurate control trajectories but require other solution techniques. Gradient-based optimization algorithms, such as the well-known sequential quadratic programming (SQP) algorithm [15], are often applied to these problems and have some superior convergence properties compared to the popular genetic algorithms, e.g. the computational load increases almost linearly with the number of controls and superlinear with the number of entries in the drive cycle. However, SQP can perform badly on problems with non-convex and disjunctive behavior because of inaccurate gradient information used to determine the search direction.

To benefit from both optimization techniques, a combination of the multi-objective genetic algorithm (MOGA) with solutions of the HOC is proposed. We call it the MOGA-HOC approach. This leads to an optimization process with four steps for each population individual:

- Non-convex multi-objective optimization of one population individual using NSGA-II [14].
- Casting the energy management problem of this design individual into a convexified HOC to generate reliable continuous and discrete control trajectories.
- Additionally, discretization of the CVT-like gear ratio control trajectory using the optimized gear set.

- Resolving the remaining continuous energy management problem as simple OCP.

The signal flow between the MOGA and (H)OCs is depicted in Figure 3.

The optimization strategy includes the steps of sizing and mass correction of the powertrain components. The principle is explained in detail in [3]. We extend the sizing problem with further restrictions to be able to cope with step two and four requiring convex optimization techniques such as SQP.

Subjective Drivability Performance Index

The subjective drivability performance index (SDPI) is a scaled weighting of the driving performance assessed by many different drivers. The SDPI is determined by computing the maximum acceleration for each gear ratio i_{gbx}^j as

$$a_{max}^j = \frac{(T_{mg}^{max}(n_{mg}) + T_{ice}^{max}(n_{ice})) \cdot (i_{gbx}^j / r_{wh}) - F_r}{m_{veh}} \quad (32)$$

Where

$$F_r = F_{fc} + m_{veh} \cdot \dot{v}$$