EVS30 Symposium
Stuttgart, Germany, October 9 - 11, 2017

Dynamic Optimization of an Operation Strategy for a Nested Powertrain System Design Approach

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Abstract

To reduce the CO_2 emissions of the new car fleet, the car manufacturer increase the releases of hybrid and battery electric vehicles. The system design for those vehicles is difficult since the topology, the size of the components and the operation strategy influences the energy consumption, the performance, the comfort and the costs. In this paper a method is presented to optimize the operation strategy regarding the minimum energy consumption of a specific vehicle, for a specific driving cycle. The developed method is valid for a P2/P4 hybrid electric vehicle and its derivatives as P2, P4 hybrid electric vehicles, four wheel and rear wheel drive battery electric vehicles as well as conventional vehicles. A modular vehicle model is developed, adaptable to each considered topology. For hybrid electric vehicles the energy consumption has to be minimized while obtaining a balanced charge of the high voltage battery. The optimization variables are the power distribution between the power sources and power sinks, the gear trajectory as well as the engine state trajectory. The properties of the optimization variables lead to a Mixed Integer - Optimal Control Problem (MI-OCP), which is solved by combining a direct and an indirect optimization method. This method is extended to solve singularities of the indirect method, caused by linear look-up table interpolation or switching decisions. Furthermore, the method is extended such that the indirect method is able to handle state constraints. Additionally, due to comfort reasons, the engine state should not be changed at high frequency and therefore time dependent state constraints are respected by the optimization method. The developed optimization method is applied on an operation strategy for a parallel hybrid electric vehicle. Compared to a reference strategy the optimized strategy reduces the CO_2 emissions by 7.8 %.

Keywords: control system, energy consumption, optimization, powertrain, simulation

1 Powertrain System Design

Powertrain System Design for hybrid and battery electric vehicles is done on three different levels. The first level is represented by the topology of the powertrain. The topology defines which components (internal combustion engine, electric machine, high voltage battery, transmission, etc.) are within the powertrain and their location. Optimizing the topology is difficult due to the large variety of different possibilities and since it is a discrete optimization it has to be solved by an exhaustive search or a genetic algorithm. Those optimization algorithms have to deal with the trade of between computational effort and the deviation from the global optimal solution. In [11] a method is presented for an automated topology modelling which creates all possible topologies due to defined requirements. Nevertheless the created models can not yet be compared quantitative to each other. Within this project only the P2/P4 hybrid topologies and its derivatives are considered. The second level defines the sizing of the components. Compared to the topology optimization the component sizing optimization might be convex and therefore can be optimized by a gradient based optimization method. In [10] different optimization algorithms as a Genetic Algorithm, Sequential Quadratic Programming, Particle Swarm Optimization and Pattern Search are compared to the result of a brute force search. The presented method in this paper does not optimize the size of the components but can be used for comparing the energy consumption of different component sizes to each other. The third level is described by the operation strategy. The operation strategy controls the engaged gear, the engine state and the torque distribution. This paper presents a general optimization method for the operation strategy that is adaptable to different topologies. Those three levels highly influences each other and finding the most suitable powertrain regarding the energy consumption, the performance, the comfort and the costs will only lead to an optimal solution if the optimization of those levels are coupled to each other [12].

This paper is structured as follows. First a modular vehicle model is designed and the optimal control problem is formulated leading to a Mixed-Integer Optimal Control Problem. Afterwards common optimization methods for operation strategies are presented and a novel optimization method is developed for solving the presented Mixed-Integer Optimal Control Problem. At the end an optimized operations strategy is compared to a reference strategy at a P2 hybrid electric vehicle and furthermore the optimization method is used for comparing the energy consumption of different derivatives of the P2/P4 topology to each other.

2 Modular Vehicle Model

The objective of the project is to compare the energy consumption of different vehicle concepts to each other. The considered topologies are parallel hybrid electric vehicles such as a P2,P4 and P2/P4 hybrid, battery electric vehicles that are driven by the rear axis, front axis and both axes, as well as conventional vehicles. The correlation of the mentioned topologies is that all of them can be derived from a P2/P4 hybrid. This advantage is used within this project by implementing a modular P2/P4 hybrid as shown in Fig. 1 such that the other topologies can be created by removing single modules of the P2/P4 hybrid. For example the battery electric vehicle with a four wheel drive is derived by the P2/P4 hybrid by removing the internal combustion engine or the P2 hybrid from the P2/P4 hybrid by removing the electric powertrain on the front axis etc. Additional, the modules of the vehicle are implemented in a way such that they are valid for all topologies and component sizes. This has the advantage that the different vehicle concepts use the same model with different sets of parameters. Furthermore, components that appear twice in the vehicle such as the gearboxes, electric machines etc, are using the same module with different sets of parameters. In the figure the gearbox is abbreviated by 'GB', the electric machine by 'EM', the internal combustion engine by 'ICE', the front axis by 'FA' and the rear axis by 'RA'.

3 Optimal Control Problem

In general an optimal control problem (OCP) is defined by a cost function J which depends on the state trajectories $\mathbf{x}$, extraneous inputs $\mathbf{r}$ and the control inputs $\mathbf{u}$, as in Eq. (1). The change of the states $\dot{\mathbf{x}}$ is a function dependent of the states, extraneous inputs and control inputs, as in Eq. (2). The initial states $\mathbf{x}(0)$ are described by a parameter $\mathbf{x}_0$, as in Eq. (3), and the final states $\mathbf{x}(T)$ can be constrained by a parameter $\mathbf{x}_f$, as in Eq. (4). Additionally the range of the states $\mathbf{X}$ are defined by Eq. (5) and the range of the inputs $\mathbf{U}$ by Eq. (9). Within this paper bold printed variables represent vectors.

$$\min_{\mathbf{u}(t)} J(\mathbf{x}(t), \mathbf{r}(t), \mathbf{u}(t)) \tag{1}$$

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{r}(t), \mathbf{u}(t)) \tag{2}$$

$$\mathbf{x}(0) = \mathbf{x}_0 \tag{3}$$

$$\mathbf{x}(T) = \mathbf{x}_f \tag{4}$$

The optimization variables are the power distribution, the gear trajectories and the time for switching off the internal combustion engine. Therefore the state vector for the optimal control problem can be described by the state of charge (SOC) of the battery ξ, the engaged gear φ_{GB} and the state of the internal combustion engine Θ_{ICE}.

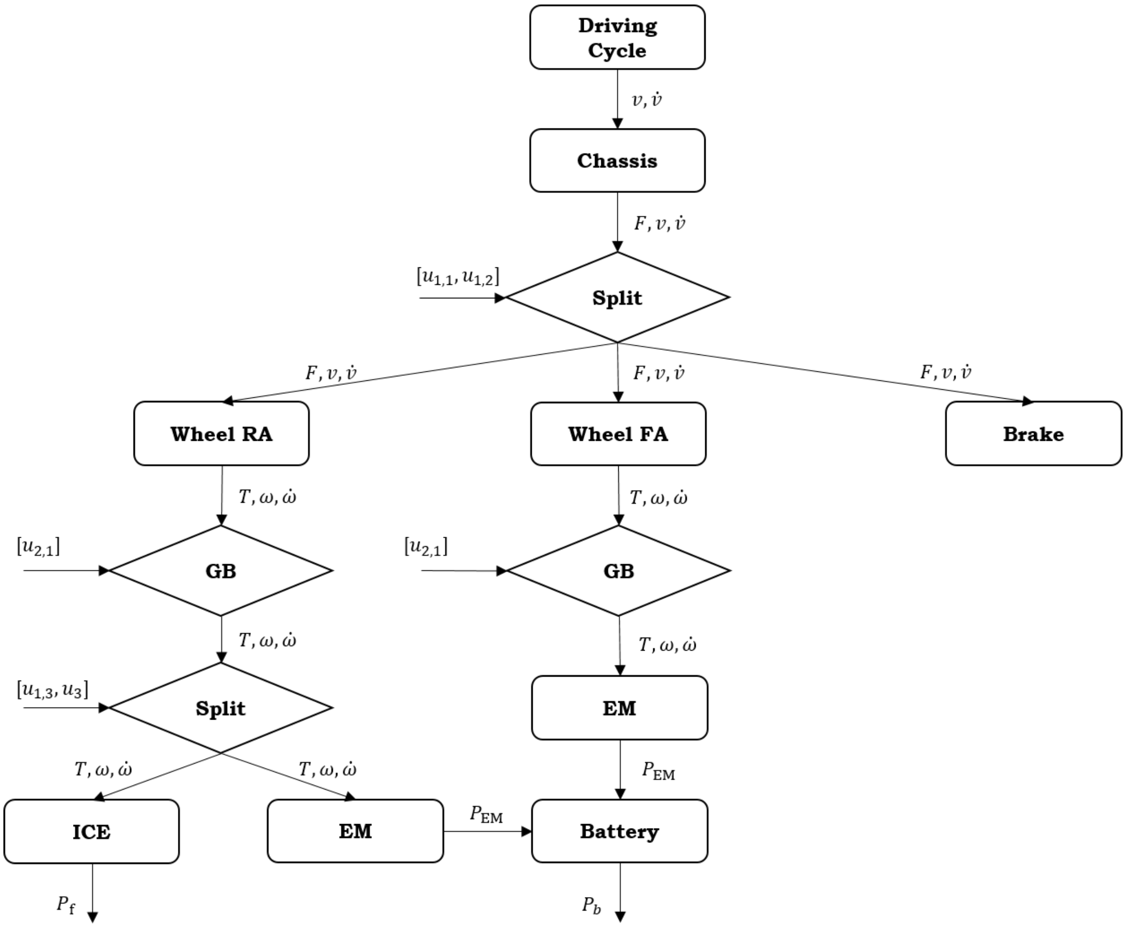

Figure 1: Signal of a modular vehicle model for a P2P4 hybrid electric vehicle.

$$\mathbf{x}(t) \in \mathbf{X}(t) \tag{5}$$

$$\mathbf{x(t)} = \begin{bmatrix} \xi(t) \\ \varphi_{\mathrm{GB}}(t) \\ \Theta_{\mathrm{ICE}}(t) \end{bmatrix} \tag{6}$$

$$\mathbf{X(t)} = \begin{Bmatrix} \xi(t) \ \in \ \mathbb{R} \mid \xi(t) \geq \underline{\xi} \mid \xi(t) \leq \overline{\xi} \\ \varphi_{\mathrm{GB}}(t) \ \in \ \mathbb{N} \mid \varphi_{\mathrm{GB}}(t) \geq \underline{\varphi_{\mathrm{GB}}} \mid \varphi_{\mathrm{GB}}(t) \leq \overline{\varphi_{\mathrm{GB}}} \\ \Theta_{\mathrm{ICE}}(t) \ \in \ \mathbb{N} \mid \Theta_{\mathrm{ICE}}(t) = 0 \mid \Theta_{\mathrm{ICE}}(t) = 1 \end{Bmatrix} \tag{7}$$

The state of charge of the battery ξ is a real number between 0 % and 100 % but often constrained by an additional lower $\underline{\xi}$ and upper bound $\overline{\xi}$. The engaged gear is a natural number between the lowest gear $\underline{\varphi_{\mathrm{GB}}}$ and the highest gear $\overline{\varphi_{\mathrm{GB}}}$. The state of the engine is described binary and either on or off.
Extraneous inputs are given by the driving cycle, can not be influenced by the control inputs and are assumed to be known a priori. For this project the velocity profile v, the acceleration $\dot{v}$ and the slope of the road α are handled as extraneous inputs as shown by Eq. (8).

$$\mathbf{r}(t) = \begin{bmatrix} v(t) \\ \dot{v}(t) \\ \alpha(t) \end{bmatrix} \tag{8}$$

As described before, the control inputs are able to split the power of the power sources, change the engaged gear and change the engine state. Splitting the power at a P2/P4 hybrid vehicle can be done by three power sources and one power sink. Therefore three control variables are necessary. The control inputs for the power distribution are $u_{1,1},\ u_{1,2},\ u_{1,3}$, the control input for changing the gear is represented by u_2 and the control variable for changing the engine state by u_3. The control inputs can be varied freely as long as the model components stay within their physical limits.

$$\mathbf{u}(t) \in \mathbf{U}(t) \tag{9}$$

$$\mathbf{u}(t) = \begin{bmatrix} \text{split power} \\ \text{shift gear} \\ \text{start/stop engine} \end{bmatrix} = \begin{bmatrix} u_{1,1}(t) \\ u_{1,2}(t) \\ u_{1,3}(t) \\ u_2(t) \\ u_3(t) \end{bmatrix} \tag{10}$$

$$\mathbf{U}(t) = \begin{Bmatrix} u_{1,1}(t) \ \in \ \mathbb{R} \mid u_{1,1}(t) \geq \underline{u}_{1,1} \mid u_{1,1}(t) \leq \overline{u}_{1,1} \\ u_{1,2}(t) \ \in \ \mathbb{R} \mid u_{1,2}(t) \geq \underline{u}_{1,2} \mid u_{1,2}(t) \leq \overline{u}_{1,2} \\ u_{1,3}(t) \ \in \ \mathbb{R} \mid u_{1,3}(t) \geq \underline{u}_{1,3} \mid u_{1,3}(t) \leq \overline{u}_{1,3} \\ u_2(t) \ \in \ \mathbb{N} \mid u_2(t) \geq -1 \mid u_2(t) \leq 1 \\ u_3(t) \ \in \ \mathbb{N} \mid u_3(t) \geq -1 \mid u_3(t) \leq 1 \end{Bmatrix} \tag{11}$$

Further limitations are defined on the running time of the internal combustion engine. A high frequent change of the engine state should be avoided due to comfort reasons. Therefore the engine state has to remain at least for a defined time span on a constant value before it is changed again.

Using the general description by Eq. (1) and adapting it to the energy management system of a vehicle leads to the cost function as defined in Eq. (12), which minimizes the time integral of the total power loss $P_{\text{loss,tot}}$ by the control inputs. The total power loss is defined as the sum of the fuel power and the electric power. The fuel power is calculated by the fuel mass flow $\dot{m}_f$ multiplied my the heating value of the fuel H_{LVH} and the electric power is calculated by the voltage U_{bat} and the current I_{bat} of the battery, as described in Eq. (13).

Furthermore hybrid electric vehicles should be analysed in a charge sustaining driving mode and therefore the constraints on the final state of charge $\xi(T)$ are defined by Eq. (14). To sum up the goal is to find the optimal input $u^\star$ which minimizes the cost function as shown in Eq. (15).

$$\min_{\mathbf{u}} J(\mathbf{x}(t), \mathbf{r}(t), \mathbf{u}(t)) = \min_{\mathbf{u}} \int_0^T P_{\text{loss,tot}}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{r}, t)\mathrm{d}t \tag{12}$$

$$P_{\text{loss,tot}} = \dot{m}_f H_{\text{LVH}} + U_{\text{bat}} I_{\text{bat}} \tag{13}$$

$$\xi(T) \geq \xi(0) \tag{14}$$

$$u^\star(t) = \arg\min_{\mathbf{u}} J(\mathbf{x}(t), \mathbf{r}(t), \mathbf{u}(t)) \tag{15}$$

The described optimal control problem contains states and control inputs in a set of real numbers (continuous range) as well as natural numbers (integer or binary variables). In literature a problem in such a form is known as Mixed Integer - Optimal Control Problem [5, 15, 8, 9]

4 Optimization Methods for Hybrid Operation Strategies

Common dynamic optimization methods, used for energy management systems, are the Dynamic Programming approach as a direct method and Pontryagin's Minimum Principle as an indirect method. The direct approach has the advantage to be a deterministic method that guarantees finding the global optimal solution independent of the described optimal control problem. The disadvantage is that the computation time increases exponentially by the number of states and the grid size. Additionally the solution contains a numerical error, also dependent on the grid size [1, 3, 13]. On the other hand the indirect approach has the advantage of short computation times and, assumed the Hamiltonian is convex, it is able to find the global optimal solution. The disadvantage is that special attention has to be paid for dealing with switching decisions, singularities and state constraints [2, 3, 4].

5 Scientific Contribution

In this paper the advantages of the direct method are combined with the advantages of the indirect method, such that the indirect method is used for optimizing the state trajectories described by real numbers and the direct method for optimizing the state trajectories described by natural numbers. A similar method is described by [9] by implementing a branch and bound method for optimizing the switching decissions and in [6, 7] a similar method is implemented that combines a direct and an indirect method, too. The methods described in [6, 7] are aiming for real-time capable systems and therefore in [6] a controller is implemented for tuning the value of the multiplier in order to obtain a balanced charge of the high voltage battery. In [7] the control problem is formulated by convex approximations such that the problem can be solved by a convex optimization method. The disadvantage of the described method regarding the objective in this project is, that implementing a controller for tuning the value of the multiplier and an approximation of the control problem can not guarantee the global optimal solution any more. Compared to [6, 7] in this project a direct and an indirect optimization method are combined to achieve a global optimal solution. Furthermore, in this project a novel method to determine the value for the Lagrange multiplier is developed, time dependent and time independent state constraints are respected and the method is extended to solve singular solutions.

6 Novel Optimization Method

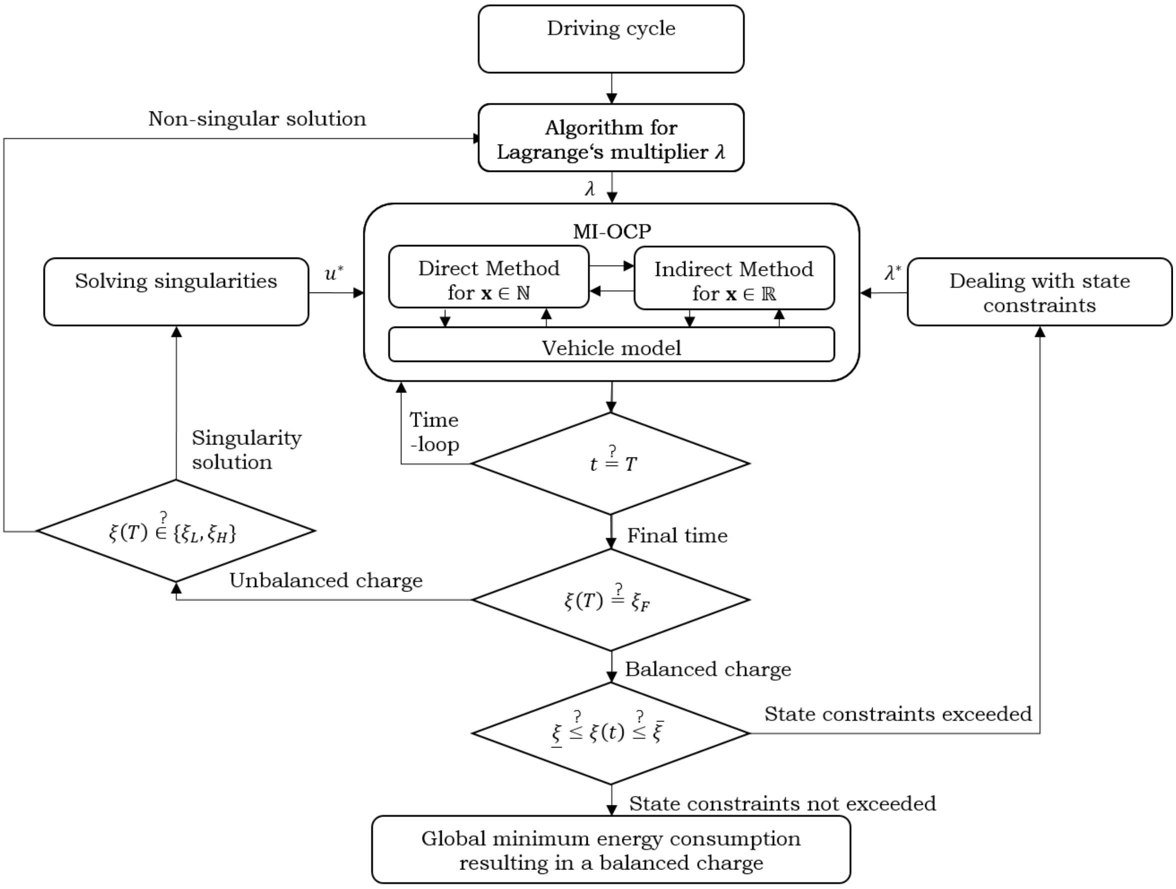

Figure 2: Work flow of the total optimization method.

Fig. 2 shows the work flow of the total optimization method. The first block 'Driving cycle' defines the velocity profile of the simulation. In the block 'Algorithm for Lagrange's multiplier λ' a value for the multiplier is estimated. This estimation is based on the relation of the fuel power to the battery power. The 'MI-OCP' is solved by combining the direct and the indirect method based on the branch and bound method of [9]. The block 'MI-OCP' is carried out until the final time step is reached $t = T$. If the final state of charge $\xi(T)$ is not equal to the desired final state ξ_F, the solution is compared to previous solutions above the final state of charge ξ_H and below the final state of charge ξ_L. In case of equal solutions a singularity is detected, which is solved in the block 'Solving Singularities'. Singularities are solved by a switching time optimization, based on [2, 9]. If the final state of charge is equal to the desired final state $\xi(T) = \xi_F$ the optimal state trajectory is controlled to be within the state constraints $\underline{\xi} \leq \xi(t) \leq \bar{\xi}$. Exceeded state constraints are treated in the block 'Dealing with state constraints'. The method for dealing with state constraints is based on [4, 14] and adapts the multiplier for specific time segments. If the state constraints are not exceeded the solution is valid and the minimum energy consumption guaranteeing a balanced charge of the high voltage is found.

7 Results

7.1 Compare the optimal strategy to a reference strategy

In Fig. 3 a strategy for a P2-hybrid is shown. Within this paper the strategy is applied to the vehicle model and presents the reference strategy. Up to time step $t = 814$ s the reference strategy is driving electric. Afterwards, the internal combustion engine is turned on and by a load point shift used in its most efficient area and therefore the high-voltage battery is charged. The braking energy gets recuperated by the electric machine in every deceleration situation.

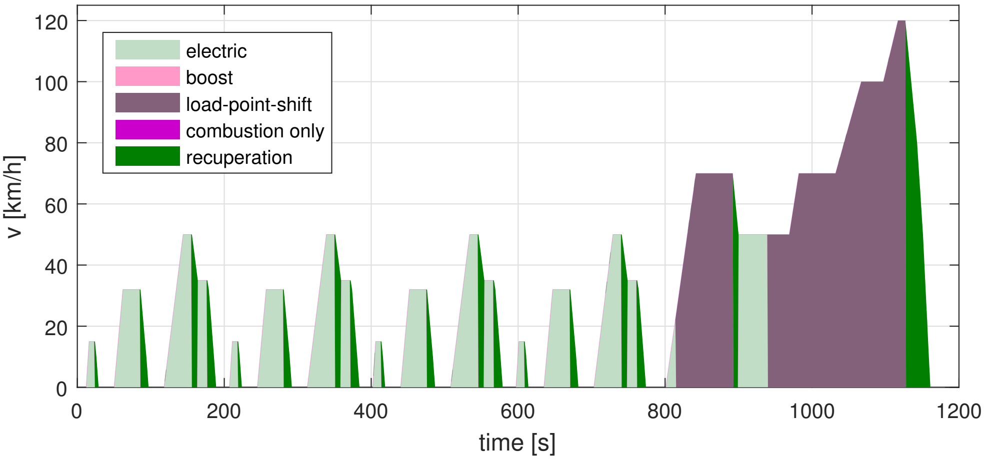

Figure 3: Velocity profile of the NEDC where the reference strategy defines the driving mode for each segment.

Afterwards the optimization method is used for optimizing the energy management strategy. The optimal strategy is shown in Fig. 4. Compared to the reference strategy the optimal strategy drives combined on the acceleration ramps that lead to a velocity of 50 km/h but drives electric at a constant velocity at the NEDC highway part. The braking energy is recuperated by the electric machines, too.

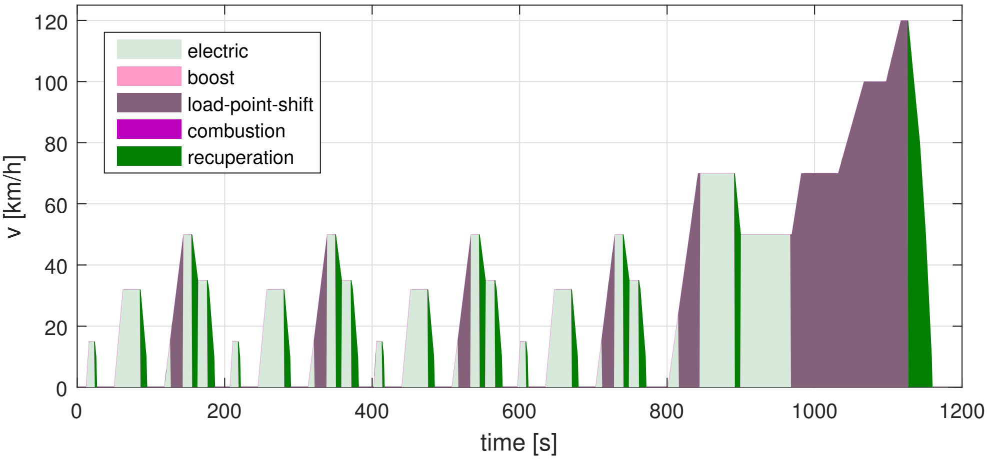

Figure 4: Velotcity profile of the NEDC where the optimal strategy calculated by the optimization method defines the driving mode for each segment.

The presented optimization method is applied on a parallel hybrid electric vehicle at the New European Driving Cycle (NEDC). In Fig. 5 the optimized strategy (red dashed line) is compared to a reference strategy (blue solid line). The plot on top shows the velocity profile v. The plot below shows the state

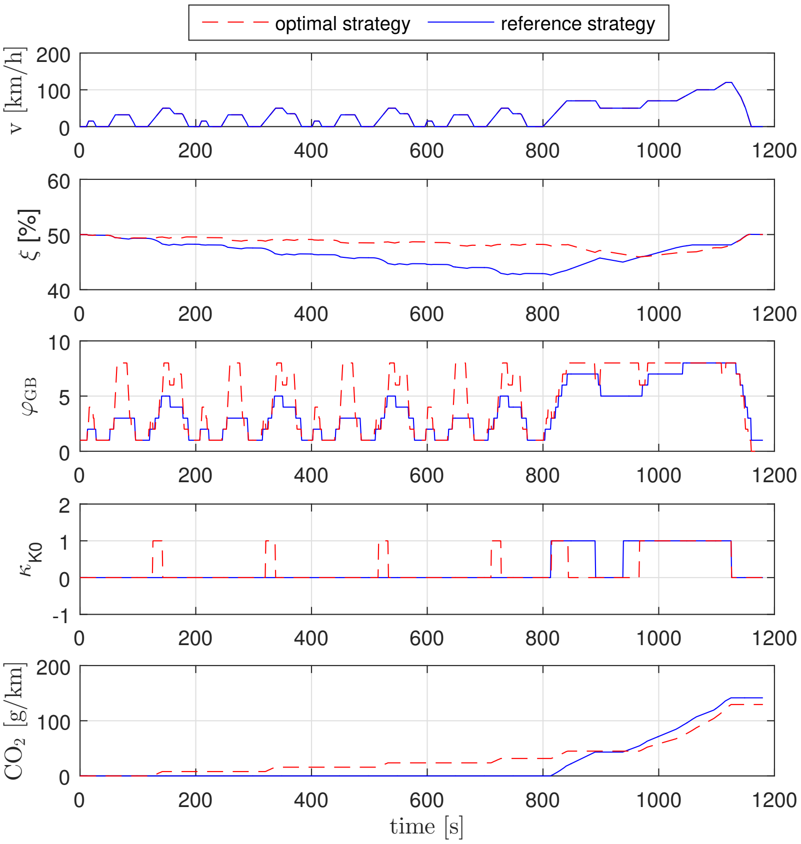

Figure 5: Comparison of the reference strategy to the global optimal strategy. The global optimal strategy saves 7.8 % CO_2 compared to the reference strategy.

of charge ξ. Below the trajectories of the engaged gears φ are shown. The fourth plot from the top shows the engine state Θ_{ICE}. The last plot the CO_2 emissions. The optimal strategy uses a combined driving mode for the acceleration ramps, resulting in a velocity of 50 km/h, but on the other hand drives the constant velocity parts of the highway part electric. Furthermore the optimal strategy selects higher gears, while electric driving, than the reference strategy. The optimal strategy leads to 7.8 % less CO_2 emissions compared to the reference strategy.

7.2 Compare different topologies

With the developed optimization method and the modular design of the optimization problem different vehicle concepts can be compared. Within this section four different vehicle concepts are compared to each other. First, the gear trajectory and the start-stop strategy of a conventional vehicle with an 8-speed transmission is optimized. Afterwards, the same basic vehicle is extended to a P2 Hybrid by adding an electric machine on the rear axis connected to a high voltage battery. Considering the P2 Hybrid next to the gear trajectory and the start-stop strategy, the power distribution between the internal combustion engine, the electric machine and the mechanical brake is optimized. Next, the electrification is broadened by adding a second electric machine on the front axis and the optimization method considers an additional power distribution. The last considered topology in this section is a four wheel driven battery electric vehicle created from the P2/P4 Hybrid by removing the internal combustion engine at the rear axis. For the battery electric vehicle the 8-speed transmission is replaced by a 2-speed transmission. Considering the battery electric vehicle, the gear trajectory as well as the power distribution between the electric machines on the front and rear axis as well as the mechanical brake is optimized. Even though there are differences in reality the chassis and the weight of all topologies is assumed to be constant in order to optimize under similar conditions. Next, the capacity of the battery for the battery electric vehicle is kept constant compared to the P2 and P2/P4 Hybrid. For a battery electric vehicle this capacity too small since the capacity would lead to an electric range of 55 km in the NEDC. Finally, a minimum running time of the internal combustion engine of eight seconds is implemented and the final state of charge of

the high voltage battery for the hybrid versions has to lie between 50 % and 50.5 % at an initial state of charge of 50 %.
In Tab. 1 the results of this comparison arew shown for the NEDC. At first, the computation time needed is shown in the third column. The conventional vehicle as well as the battery electric vehicle are optimized within a few seconds while the hybrid variants need more computation time to find the value of the multiplier which guarantees a balanced charge of the high voltage battery. Furthermore, the computation time rises with the number of optimization variables. In the fourth column the final state of charge of the battery is presented. While the two hybrid variations reach a final state around 50.2 % the battery electric vehicle needs nearly 20 % of the whole capacity to drive the cycle once. The CO_2 emission in the last column shows that the P2 Hybrid is able to reduce the CO_2 consumption by 43.5 % and the P2/P4 Hybrid only by 42.7 %.

Vehicle	**cycle**	**computation time**	**Final SOC**	**relative CO_2 emissions**
Conventional	NEDC	46 s		100 %
HEV P2	NEDC	1585 s	50.2 %	56.5 %
HEV P2/P4	NEDC	7230 s	50.2 %	57.3 %
BEV 4WD	NEDC	138 s	30.2 %	

Table 1: Results of the optimization for BEV 4WD, PHEV P2, PHEVP2P4

	conventional	**P2 Hybrid**	**P2P4 Hybrid**	**BEV 4WD**
ICE	82.4 %	37.4 %	37.5 %	
Battery		0.4 %	0.5 %	0.3 %
EM RA		4.2 %	2.4 %	2.4 %
EM FA			2.2 %	1.2 %
Gearbox RA	2.6 %	3.1 %	2.3 %	1 %
Gearbox FA			0.9 %	0.6 %
Auxiliary systems	1.3 %	1.3 %	1.3 %	1.3 %
Wheels	1.2 %	1.2 %	1.2 %	1.2 %
Air resistance	4.1 %	4.1 %	4.1 %	4.1 %
Roll resistance	4.2 %	4.2 %	4.2 %	4.2 %
Brake losses	4.2 %	0.1 %	0.1 %	0.1 %
Total	**100** %	**56** %	**56.6** %	**16.3** %

Table 2: Energy losses of the single components the four considered topologies at the NEDC.

In Fig. 2 the losses of the single components of the four topologies are shown relative to the total energy consumption of the conventional vehicle. Summing up the losses from the rolling resistance, air resistance, friction losses of the wheels and the energy required for the auxiliary systems gives a sum of 10.8 % of the losses which are equal for all four topologies. Since the conventional vehicle is not able to recuperate the braking energy, the brake losses of the conventional vehicle are 4.2 % while the brake losses of the electrified vehicles are 0.1 %. The electrified vehicles do have to break mechanically in special driving situations as for example, a deceleration by a vehicle speed below 7 km/h. The losses of the gearbox on the rear axis of the conventional vehicle are 0.5 % lower at the P2 Hybrid even though the model is exactly the same. This difference results out of another shifting strategy of the hybrid vehicles, since the electric machine can operate at lower speed than the electric machine. For the P2/P4 hybrid the sum of the losses of the gearbox of the front and the rear axis sum up to nearly the same losses as the losses of the gearbox of the P2 Hybrid. Due to the 2-speed transmission the losses of the gearbox of the battery electric vehicle are less compared to the 8-speed transmission. The combined losses of the two electric machines of the P2/P4 Hybrid are slightly higher than the losses of the electric machine of the P2 Hybrid. While combining two electric machines the power between those both machines can be optimized but the losses of both electric machines get added. The numbers for the efficiency in the table indicate that distributing the power of the electric machines can not equalize the extra losses of the extra electric machine and therefore lead to a higher loss power. The losses of the electric machines of the battery electric vehicle are less than those of the hybrid vehicles even though the battery electric vehicle drives a longer distance electric. Due to the load point shift the electric machines of the hybrid vehicles are recuperating much more energy than the electric machines at the battery electric vehicle. Since recuperating energy by the electric machines also leads to losses, the total efficiency of the electric machines of the hybrid vehicles are worse compared to the battery electric vehicle. The battery losses of the hybrid and the battery electric vehicle are nearly similar. The greatest difference of the losses are at the internal combustion engine. While the conventional vehicle has engine losses of 82.4 % the losses at the hybrid vehicles are less than the half of the conventional vehicle around 37.5 %.

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