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Transportation Research Procedia 14 (2016) 3611 – 3620

Transportation Research Procedia

www.elsevier.com/locate/procedia

6th Transport Research Arena April 18-21, 2016

Electric powertrain system design of BEV and HEV applying a multi objective optimization methodology

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Abstract

In this paper a complete vehicle system simulation tool chain which applies a Multi Objective Optimization (MOO) methodology for designing the Electric Powertrain (ePT) of Battery Electric Vehicles (BEV) is presented. Optimization scope includes all relevant electric powertrain components from battery, inverter, electric machine to gear box. In addition to cost, vehicle dynamics, energy consumption and range are further optimization targets. For an overall minimal system cost design a multiplicity of interactions between all powertrain components has to be taken into account. High system complexity prevents an expert to consider all relevant correlations without the support of numeric simulation tools. The presented simulation tool chain enables fast identification of the best cost/benefit trade off regarding system cost while considering all defined system performance requirements. The approach enables experts to find unconventional solutions which would have been overlooked applying a classical straight forward approach and, thus, helps to sharpen the expert's knowledge in cause-effect relationships on the system level. Typical use cases are given and illustrated by several practical examples.

Peer-review under responsibility of Road and Bridge Research Institute (IBDiM)

Keywords: Vehicle system simulation; Battery Electric Vehicles (BEV); Multi Objective Optimization (MOO)

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Peer-review under responsibility of Road and Bridge Research Institute (IBDiM)
doi:10.1016/j.trpro.2016.05.429

1. Introduction

A profitable business model for Battery Electric Vehicles (BEV) as well as a sustainable reduction of CO_2 emissions requires a significant increase in production volume of vehicles with electric powertrains (ePT). Besides technical barriers, such as acceptable vehicle range and comfortable concepts for battery charging, a considerable cost reduction of ePTs must be achieved. Since traction battery costs are the largest contributor, reducing these costs has the most leverage to significantly increase market acceptance of BEVs.

Efforts generally strongly focus on achieving cost reductions of single components like traction battery, inverter and electric machine itself. Significant cost reductions have already been achieved but are still not sufficient for sustainable market penetration. Large efforts are made to systematically research new technologies, such as high energy battery cells, as well as improved design and manufacturing concepts (Liebl et al. (2014), Fink et al. (2015)).

In most cases minimizing the cost of single components does not lead to an overall minimal system cost design. In contrast interactions between ePT components are often underestimated. As shown in Fig. 1, the technical performance and total cost of the ePT are influenced by a multitude (more than 15) of system relevant component parameters.

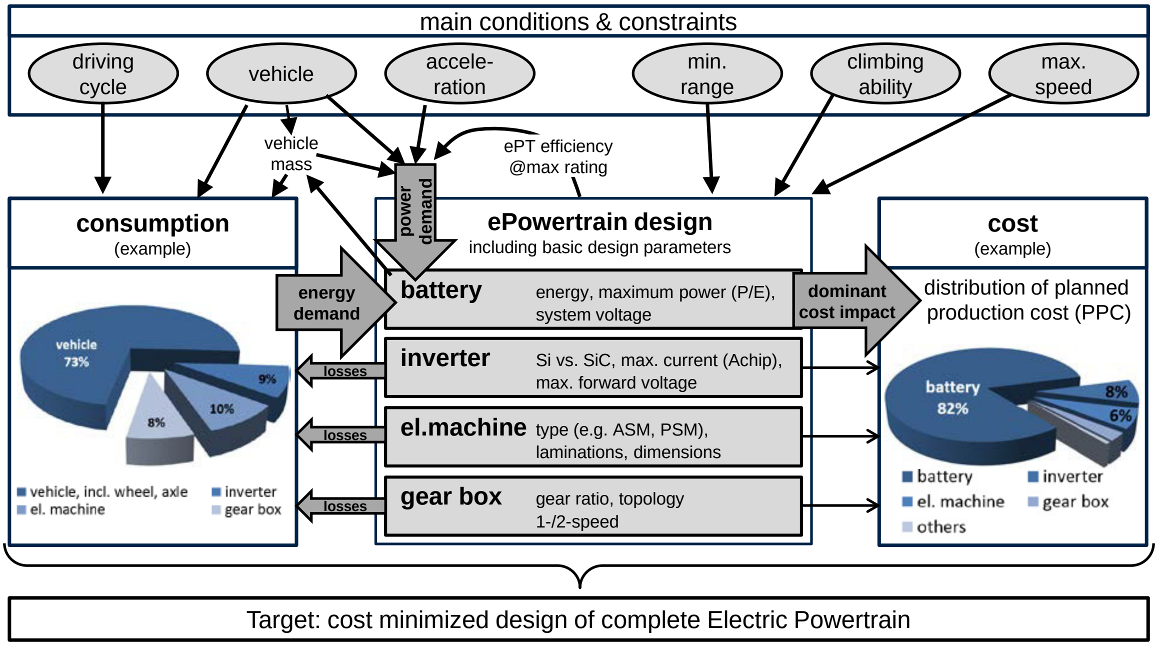

Fig. 1. Requirements, design parameters and correlations between efficiency and system cost in Electric Powertrains (ePT).

For an overall minimal system cost design a plurality of interactions between these parameters must be taken into account. Example: Vehicle energy consumption has a strong impact on battery cost, which has the largest share in system cost. Vehicle consumption itself is strongly influenced by all components of the electric powertrain. Hence additional cost for a more efficient machine or inverter can often be more than compensated by savings in the significantly more expensive battery.

Due to high system complexity it is not possible for an expert to consider all relevant correlations for a minimal system cost design with given requirements and premises on vehicle level. Therefore a simulation-based system development approach using a Multi Objective Optimization (MOO) methodology is presented in this paper.

2. Methodology

2.1. Overview

An overview regarding the structure and workflow of a simulation tool using MOO applied to the design of ePTs with the main target to minimize overall cost is shown in Fig. 2. A system optimization contains three steps:

- Simulation setup: An initial definition of optimization targets, vehicle requirements, parameter ranges and assumptions (or boundary conditions).
- System simulation & optimization: Evaluation of cost and technical performance for a variety of different system designs (e.g. 50.000) determined by a genetic optimization algorithm.
- Analysis of results: Establish Pareto front of best designs regarding all defined optimization targets.

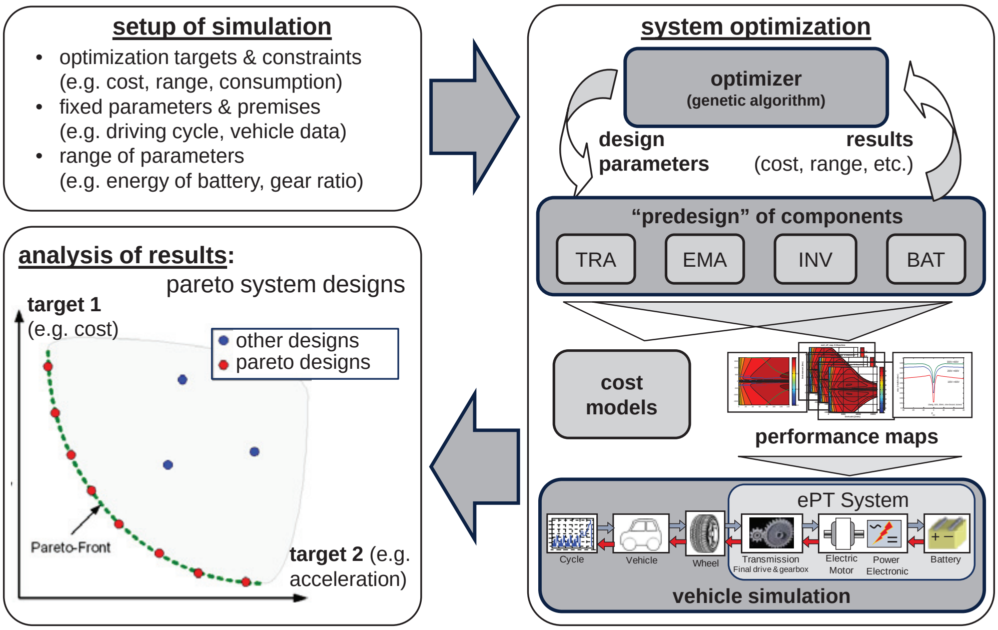

Fig. 2. Structure of simulation based system optimization using the methodology of Multi Objective Optimization (MOO).

2.2. Vehicle requirements, optimization targets and boundary conditions

The required ePT performance is defined by vehicle performance requirements. Some fundamental vehicle requirements are listed in Table 1.

Table 1. Fundamental vehicle requirements for the Electric Powertrain of BEVs.

Vehicle Requirement	Typical Values
Acceleration	Typically time from 0 km/h to 100km/h, value depending on vehicle class.
Maximum vehicle velocity	E.g. 160 km/h, depending on vehicle class and target market.
Range	Today typically <200 km; in the next years larger values are expected.
Gradeability	Slope in % at given speed.
Drive off on slope	Slope in % for drive off with maximum load and given acceleration.
Drive up curb	Optional requirement, typically up to 100 mm step height.
Further drivability requirements	E.g. acceleration time from 80 km/h to 120 km/h or engine power at maximum speed.

Further requirements and boundary conditions which have an impact on the ePowertrain design among others are

- Vehicle class and data as well as driving cycle for energy consumption (e.g. NEDC, WLTC[1]).
- Thermal conditions depending on vehicle cooling system.
- Constraints due to the mounting position inside the vehicle, e.g. mechanic stress in case of accident.

To setup a system optimization, all parameters and requirements mentioned above have to be defined or set as an optimization target (see chapter 2.4). Minimizing cost is nearly always a target in system simulation.

2.3. Simulation procedure

Target of system optimization is to identify designs that meet all requirements and constraints while achieving best scores regarding their target values (e.g. cost and acceleration). Therefore an optimizer based on a genetic algorithm determines design parameters within the pre-defined range established during setup.

Next, the technical limits, performance maps and cost of all components are calculated for the given set of parameters. A map based vehicle model is configured with the output data from predesign models. The vehicle performance is evaluated by running different test cases such as driving cycle simulations (efficiency, range) and acceleration tests.

After design evaluation, the resulting performance values are provided as feedback to the optimizer. New sets of parameters are identified and evaluated. With two optimization targets, a fully converged result can be achieved after around 50,000 evaluated designs, depending on the number and range of variable design parameters. Simulation time can be reduced by parallel computing of single designs on several cores. Further information on optimization algorithms as well as its application on vehicle level can be found in Coello et al. (2007), Deb et al. (2011) and Martin et al. (2015).

2.4. Analysis of results

After all simulation runs are finished, ePT designs with the best performance values regarding all target parameters are plotted in a Pareto front (see Fig. 2). In case of two targets, the Pareto front is a curve that demonstrates the tradeoff between each target. E.g. if cost and acceleration are targets and a design on the Pareto front has an acceleration value of 8 seconds, this design on the Pareto front has the lowest cost which achieves the required acceleration performance.

2.5. Further vehicle topologies

The system design methodology can also be applied to further vehicle topologies such as Hybrid Electric Vehicles (HEV) or BEVs with 2 or more electric machines (Kuchenbuch et al. (2011), Appel et al. (2014), Buerger et al. (2010), Buerger et al. (2012), Schulte-Cörne (2015)). Typical optimization targets for HEVs are CO_2 emissions evaluated with regards to the target certification procedure, e.g. WLTP. In topologies with more than one drive unit, a control strategy to split the total power demand is essential, that can also be included in the scope of optimization.

3. Simulation models

3.1. Scalable models for component predesign

Detailed and scalable physical predesign models based on well-established cross-domain expert knowledge are necessary to evaluate the impact of components with a specific set of parameters on the vehicle performance. A schematic illustration of a predesign model for an electric machine is shown in Fig. 3.

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[1] NEDC: New European Driving Cycle; WLTC: Worldwide harmonized Light vehicles Test Cycle.

A technical predesign model calculates the machine performance maps needed to perform the vehicle system simulation based on a given set of parameters, e.g. machine type, lamination geometry, diameter and magnetic length. The performance maps include efficiency, phase current and power factor as a function of machine torque, machine speed and battery voltage. Furthermore, machine limits such as maximum torque and speed are included. An algorithm is applied to determine efficiency optimized machine control at each operating point during the predesign. Additionally a part list based on all machine parameters is generated to estimate the machine cost.

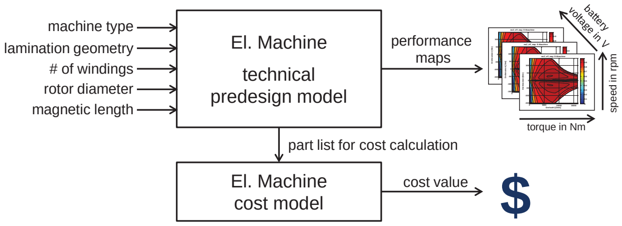


Fig. 3. Schematic illustration of scalable technical and cost predesign models for an electric machine.

Predesign models must have a low computation time, since nearly 50,000 designs have to be evaluated for a single optimization run. Hence simulation models based on finite elements are not suitable. Therefore significant effort has been made to achieve fast calculating predesign models especially for the electric machine and the gear box based on empirical-physical models.

Table 2 gives an overview of all components and their scalable design parameters as well as their outputs for design evaluation. In general the technical behavior of a component depends on many more parameters. In order to reduce complexity of the whole system during the optimization, it is important to reduce the number of scalable parameters, e.g. as a result of sensitivity analysis.

Table 2. Overview of scalable models for component predesign.

component of ePowertrain	**scalable design parameters**	**output for design evaluation**
battery	cell type; cell capacity in Ah value; number of cells (parallel/serial)	voltage maps; resistant maps; current limits; energy content; bill of materials; cost
inverter	semiconductor type; max. forward voltage; area of semiconductor dies	current and voltage limits, loss maps, bill of materials; cost
electric machine	machine type; lamination geometry incl. number of poles; rotor diameter; magnetic length; number of windings	torque and rotation speed limits; efficiency maps; control maps (voltage, current, cos φ); cost
gear box	# of gears; gear box topology; max. torque; gear ratio(s)	efficiency maps; cost

3.2. Cost models

The principle target of system optimization is to identify the least expensive ePT design for a given set of vehicle performance requirements. For a cost driven system design evaluation cost models have been derived from credible data based on series production plants for several existing production designs. Relevant manufacturing steps and the highest cost parts were identified and the respective cost dependencies derived. Cost models estimate an expected planned production cost (PPC) depending on the part list provided by the technical predesign models (see Fig. 3).

3.3. Vehicle Simulation

Vehicle performance characteristics (energy consumption, acceleration ability, etc.) for a given vehicle system can be identified by applying numeric vehicle simulation. An object oriented model structure offers an efficient methodology to construct drive train topologies with standardized interfaces. These vehicle models are based on extensive component libraries (electrical machines, battery systems, etc.). Further benefits of the object oriented methodology are standardized model structures as well as efficient model maintenance.

Map based models for the electric machine and mechanical transmission subsystems are integrated to describe their respective technical characteristics. The required characteristic maps (power loss maps, generator and motor limiting curves, etc.) are derived based on previous calculations for each component (see also chapter 3.1) and are used in the next vehicle simulation. The initial estimate assumes an optimal control strategy by the power electronics (inverter) for the electric machine. Inverter losses are calculated based on the electric machine characteristic maps (power factor cos phi, phase current and voltage maps).

The traction battery model is based on an electrical equivalent circuit diagram. Hence each battery cell is characterized by a resistance element, which reflects the cell's inner resistance. Characteristic maps describe both inner resistance and open circuit voltage of each cell. In this manner both state of charge (SOC) and temperature dependencies are taken into consideration. Separate maps are utilized for charging and discharging. In addition, the battery model integrates the battery management which monitors and ensures the state (current and voltage) of each cell. As a result of battery model structure based on an electrical equivalent circuit diagram, scaling with respect to number of serial and parallel cells is possible.

The physical based vehicle model takes all subsystem interactions into account. Interdependent interactions between drive train components and vehicle chassis (chassis and tires) and furthermore to the vehicle's environment are all taken into account. The vehicle acceleration is calculated in the simulation per each numeric integration step by opposing the driving force to the driving resistance. The vehicle speed control is realized by a generic driver, for which a feed-forward model approach is required. This approach allows the identification of energy savings potential on vehicle system level resulting from new component control strategies.

4. Use cases for computer-based optimization of electrical powertrains

In this chapter, exemplary use cases are provided. Practical examples can be found in chapter 5.

4.1. Cost optimized system design for given vehicle requirements

As already mentioned it is often very difficult to find a minimal cost system design for given requirements on vehicle level by a stepwise straight forward system design process which does not take all of the complex component interactions into account. Especially the high impact of efficiency is often underestimated. A computer based simulation tool is necessary to identify minimal cost system designs taking all interactions into account while reducing the necessary engineering effort significantly.

4.2. Benefits of different topologies or technologies on system level

For strategic planning of a product portfolio, a deep understanding regarding the impact of different topology or technology variants on the vehicle performance is essential. Examples of variants are different machine types like asynchronous induction machine (ASM) vs. permanent excited synchronous machine (PSM), gear box topology variants like spur gears vs. planetary gears or 1- vs. 2-speed gearbox as well as different semiconductor types like IGBT (insulated gate bipolar transistor) vs. SiC-MOSFET (Silicon Carbide Metal Oxide Semiconductor).

A classical approach evaluates technology or topology variants on vehicle level within a fixed electrical powertrain design. In contrast, for a balanced evaluation often all components of the electric powertrain have to be redesigned in case of a technology change within one component. This ensures that the complete benefit of the design variation is understood. E.g. to evaluate benefits of SiC-MOSEFTs over IGBT-semiconductors, it is not sufficient to change only the semiconductor type inside the inverter, but also to increase the system voltage level, as powertrains with SiC-MOSFET tend to higher system voltages than powertrains with IGBT technology (see chapter 5.2). Using the system optimization tool, it is possible to identify optimized system designs for each topology or technology variant for given requirements on vehicle level (e.g. acceleration, see chapter 5.3) including a detailed analysis of expected system cost.

4.3. Sensitivity and impact analysis: impact of varying boundary conditions on design and cost

For a strategic decision a deep understanding regarding the impact of varying boundary conditions on all components of the ePT is necessary. Here is a sample of such boundary conditions:

- changes in driving cycles
- different vehicle performance requirements, like acceleration or hill gradeability
- cost scenarios, e.g. for battery cost

5. Practical examples of system evaluations

5.1. Example 1: Evaluation of ePT topologies with 1-speed vs. 2-speed gearboxes

The investigation objective is to quantify vehicle performance benefits in a BEV with a 2-speed gearbox versus a 1-speed gearbox in a subcompact class vehicle with defined requirements. Primary optimization targets are cost and acceleration time (0 to 100 km/h). Separate optimization runs were performed for 1-speed (green dots) and 2-speed-gearboxes (black dots). A 12-pole PSM machine was chosen for this investigation. Some Pareto results for the considered ePT designs are shown in Fig. 4.

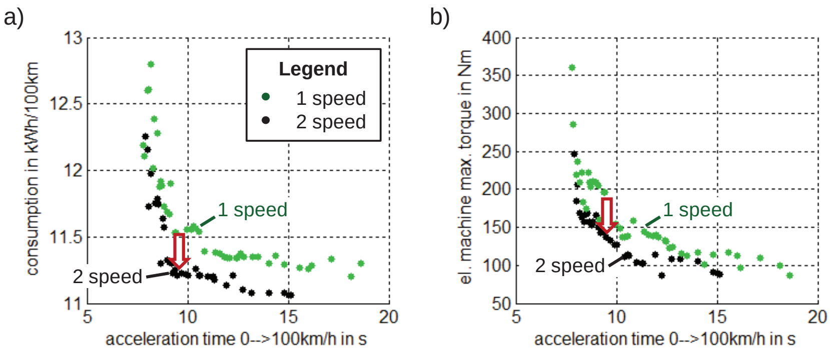


Fig. 4. Pareto fronts of 1-speed vs. 2-speed. a) Consumption vs. acceleration. b) Maximum machine torque vs. acceleration. Not considered: Additional losses from the actuator, clutch and control device for 2 speed gearbox.

Fig. 4a) shows energy consumption of optimized designs with different acceleration performance. In this example designs utilizing a 2-speed gearbox result in a 2.5% to 3% improvement in energy consumption. This value strongly depends on machine type. The efficiency increase is achieved by selecting gear ratios for both gears in a way that relevant operating points during the cycle are moved to higher efficiency operating areas. Fig. 5a) shows the operating points of NEDC within the machine efficiency map for the 1-speed gearbox. Fig. 5b) shows how the operating points with low efficiency at high engine speeds (grey dots) are moved to lower speeds and higher torques by using the lower 2nd speed gear ratio. Thus, machine losses can be reduced by approximately 20% which results in battery cost savings due to the reduced energy demand. Higher losses at higher machine speed in the field weakening range are avoided for the most part (see Fig. 5b).

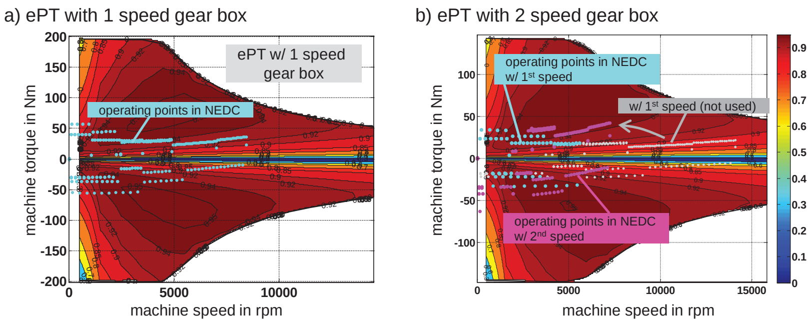


Fig. 5. Machine efficiency maps (type PSM) optimized for ePTs including operating points in NEDC w/ a) 1 gear b) 2 gears.

A further benefit of 2-speed designs is a significantly reduced machine torque requirement for a defined acceleration performance enabled by a higher gear ratio in the first gear (see 4b). Hence machine cost can be reduced, as the cost strongly depends on the maximum torque requirement. Furthermore inverter cost is reduced, based on the reduced current demand of the machine during nominal operation. These benefits are slightly offset by higher additional gearbox cost from the second speed and the additional actuator, as well as additional losses from the actuator, clutch and control device. A summary of selected performance values of both evaluated designs is shown in Table 3.

Table 3. Selected performance values of designs as shown in Fig. 5.

gear box	**max. machine torque**	**max. inverter current**	**gear ratio**	**vehicle consumption w/o climatisation**	**machine losses in NEDC**	**max. speed**	**range**	**acceleration (0-100km/h)/ (80-120km/h)**
a) 1 speed	196 Nm	325 Arms	7.73	11,5 kWh/100km	1,35 kWh/100km	192 km/h	160 km	9.3s /6.5s
b) 2 speed	143 Nm	280 Arms	12.91 / 6.63	11,2 kWh/100km	1,09 kWh/100km	190 km/h	160 km	9.3s / 6.6s

5.2. Example 2: System evaluation of different power semiconductor technologies

The investigation objective is to assess the impact of semiconductor technology used by the inverter on the ePT with respect to total system cost. In general a minimal cost design that meets all vehicle requirements for defined boundary conditions as summarized in Table 4, is desired.

A) with IGBT power semiconductor B) with SiC-MOSFET semiconductor technology.

Table 4. Set of vehicle requirements and boundary conditions for assessment of inverters featuring SiC-MOSFET.

vehicle class	**driving cycle**	**range**	**acceleration time**	**max. veh. speed**	**climbing ability**	**machine**	**battery cell**
compact class	NEDC	>160km	< 8s (0->100km/h)	>160km/h	>35%	ASM (PSM)	34Ah LiIon

Optimized system designs for both cases differ not only in the inverter design, but also with respect to system voltage level and have a strong impact on battery and machine design. IGBT designs tend to have battery voltages around 400V suitable for IGBTs capable of 650V forward voltage. Higher voltage levels lead to higher switching losses in the inverter despite reduced currents at the same power demand. In contrast, for wide band gap semiconductors like SiC-MOSFET an increased efficiency at higher voltage levels is expected (Wintrich et al. (2015), Lutz et al. (2011)). Therefore higher system voltages are expected for SiC-MOSFET rather than for IGBT. Despite expected higher battery cost resulting from increased effort for voltage monitoring within the battery control unit, an overall benefit at the system level is expected. In the given example, system designs with 650V-IGBT and 900V-SiC-MOSFET were selected.

Benefits in both cases strongly depend on inverter design and semiconductor data. Case A) leads to reduced vehicle consumption over the driving cycle and therefore to a reduced energy demand in the battery for a given range with strong cost saving potential in the battery. An overview of energy savings for different machine types and driving cycles (NEDC and WLTP) is provided in Fig.7.

Reduced losses during acceleration (case B) including the nominal operating point of the inverter, lead to designs with reduced semiconductor chip size. Benefits are reduced inverter cost and volume.

The savings in energy consumption with SiC-MOSFET are higher for ASM than for PSM due to its higher current demand for rotor excitation especially in typical operating points of driving cycles which lead to increased inverter losses with IGBT-technology.

As illustrated in Fig. 6, SiC-MOSFET- technology leads to an efficiency increase for both cases,
A) over the driving cycle and B) during acceleration.

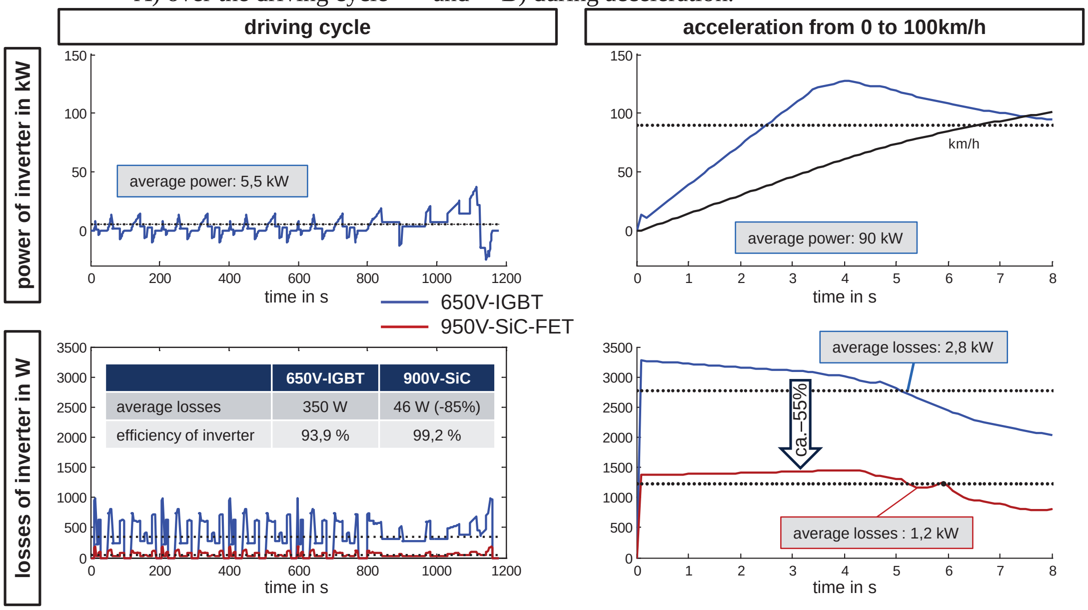
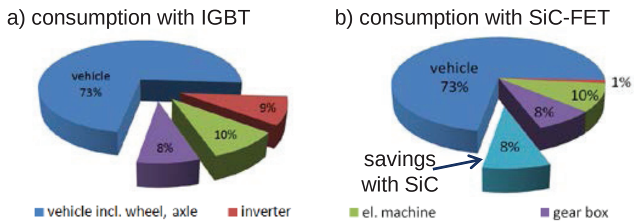


Fig. 6. Impact of inverter semiconductor technology (IGBT, SiC-FET) on losses in (a) driving cycle (b) acceleration.



c) savings in consumption with SiC-FET

Cycle	ASM	PSM
NEDC	8% +/- 0,5%	6,5% +/- 0,5%
WLTP	6,5% +/-0,5%	5,5%+/- 0,5%

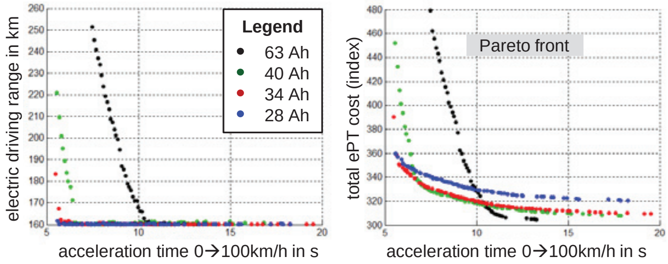
Fig. 7. Exemplary distribution of energy consumption for BEV (a) with IGBT- (b) with SiC-FET. (c) Savings in consumption with SiC-FET.

5.3. Example 3: Cost of acceleration performance in BEVs

A fundamental performance indicator for all vehicles is the acceleration time from vehicle standstill to 100 km/h. The correlation between cost and acceleration is an important factor for vehicle portfolio planning. The result of this investigation for different battery cells is shown in Fig. 8. Optimization targets were total system cost and acceleration. A minimum range of 160 km is required.

Optimizations have been performed with different cell capacities with associated power/energy (P/E) ratios as listed in Fig. 8. The 63Ah-cell has the lowest P/E ratio and has been designed for BEVs. Battery designs with any numbers of cells have been simulated in order to achieve the demanded range and vehicle acceleration.

In the left box of Fig. 8 vehicle range versus acceleration is illustrated. A certain minimum acceleration time for each battery cell type results from the associated power limits. Faster acceleration times can only be achieved by increasing the energy of the battery beyond the 160 km requirement and hence its power and vehicle range with high impact on system cost. The rise in system cost for acceleration values below this minimum acceleration time is approximately 10 times higher per second acceleration time than above this minimum. The minimum acceleration time strongly depends on the cell type.



cell capacity	C-rate discharge	min. acceleration (0 to 100km/h)
63 Ah	4	10.4 s
40 Ah	7	6.5 s
34 Ah	12	5.8 s
28 Ah	12.6	5.7 s

Fig. 8. System designs (Pareto front) with optimization targets cost vs. acceleration for different battery cell types. Vehicle class: Compact class.

Simulations show, that a well-balanced roadmap planning regarding acceleration performance, battery cell type and vehicle range is necessary for a system cost optimized product strategy.

6. Conclusion

In this paper a simulation methodology for a minimal system cost design of electric powertrains (ePTs) for Battery Electric Vehicles (BEV) is presented. Use cases for this approach are to identify minimal system cost designs that cannot be found by stepwise design approaches, by taking into account all relevant interactions between ePT every components. Furthermore profound evaluations of technology and topology variants as well as sensitivity analysis can be performed. The overall structure and workflow of this simulation tool is explained and illustrated by several examples.

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