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Optimization of Hybrid Electric Drive System Components in Long-Haul Vehicles for the Evaluation of Customer Requirements

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***Abstract*-Optimum drivetrain design is the key objective for achieving climate and economy improvements in the long-haul industry. The approach introduced focuses on the optimization of electronic component design. Not only are the longitudinal dynamics and the energy consumption included, but a detailed cost model of the components is also applied. The objective is to identify the most profitable state-of-the-art drive technologies. An evolutionary optimization algorithm combines a generic vehicle model with a cost model to calculate the Pareto optimal solutions for battery systems, electric machines and gearbox design. The results show the potential of Hybrid Electric Vehicles in comparison to diesel trucks. Fuel savings are expressed with the indicator transport efficiency in grams of CO_2 per transported ton of payload. The Total Cost of Ownership is calculated in Euros per ton kilometer.**

I. INTRODUCTION

Due to climate change and the resulting stricter laws for greenhouse emissions [1], it is necessary to reduce road vehicle fuel consumption. Yet the demand for freight traffic is increasing and road transport will remain the most important method for transporting goods [2]. Recent advances in hybrid vehicle technologies [3] and the ongoing decrease in battery prices [4, 5] have made hybridization attractive for the long-haul truck industry. One of the key figures for this price-sensitive industry is the Total Cost of Ownership (TCO). As a new technology, hybrid drivetrains must not only reduce emissions and fuel consumption, but also the TCO are to be fully accepted. This study aims to optimize the drivetrain components for a European long-haul truck concept under consideration of a highly detailed TCO model. Further, the transport efficiency is observed to take secondary effects into account, such as mass reduction. Additionally, the 60 to 80 km/h acceleration time, also called elasticity, is an objective that describes the trucks' driving dynamics. A forward simulation model calculates the fuel consumption and longitudinal dynamics [6]. Component models for costs, masses and battery life calculate the objectives for different powertrain configurations. The resulting multi-objective optimization problem (MOP), (Equation 1), is assessed with the evolutionary algorithm NSGA-II [7] to obtain Pareto optimal solutions. The contradiction between the chosen optimization objectives leads to tradeoff solutions solved by computational intelligence.

$$\text{Min } F(x) \rightarrow \text{Min}\left(f_{\text{TCO}}(x), f_{\eta,\text{Transport}}(x), f_{\text{Acceleration}}(x)\right) \quad (1)$$

The algorithm systematically alters the design variables shown in Fig. 1 to obtain sets of optimal solutions. To analyze the interaction between an internal combustion engine (ICE) and hybrid components, three different engine power classes are taken into account.

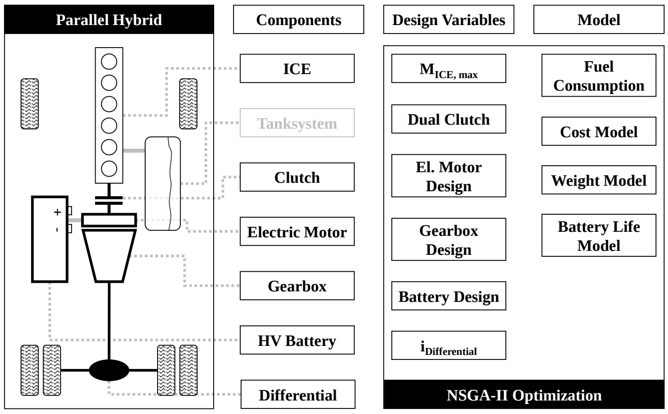

Figure 1. Parallel hybrid topology with design variables for MOP

The results show that hybrid vehicles outperform the standard diesel engine in all optimization objectives during a usage period of 6 years with an optimum set of electric components.

II. METHODOLOGY

The simulation model is validated with data from real life test runs [6] and achieves a deviation of approximately 3-5 %, depending on asphalt and weather conditions. The model uses a parallel hybrid drivetrain topology, (Fig. 1), with individual performance mappings for the ICE, electric motor (EM) and battery. Each mapping depends on characteristic values (Table I) and is completely parameterized. The gearbox model allows for a perfectly adopted gearbox design with an adjustable number of gears [8] and the possibility of an overdrive gear. The dual clutch is modelled by setting the shift time and the tractive force disruption to zero. The parametrized drivetrain model uses a closed-loop forward simulation to obtain the energy consumption for a given driving cycle [6]. A component-based mass and cost model evaluates the purchase price, resulting in the fixed costs for the TCO calculation. The energy consumption obtained in combination with models for battery life [9], as well as the average velocity during the cycle yield the TCO's variable-cost parts.

TABLE I: Design Variables for MOP

Design Variable	Unit	Range
Electric Motor Design		
Electric Motor Type	-	IM, PMSM
Electric Torque	Nm	500 – 2000
Transition Speed	min^{-1}	1000 – 1500
Battery Design		
Cell Type	-	Pouch, Prismatic
Total Capacity	Ah	10 -155
Usable Capacity	%	10 – 100
Gearbox and Clutch Design		
Number of Gears	-	8; 10; 12; 16
Spread	-	8 - 22
Overdrive	-	True, False
Dual Clutch	-	True, False
Rear Axle Ratio	-	2.5 – 3.5

Fig. 2 displays the optimization framework interacting with the closed-loop forward simulation model. The simulation is used in combination with the generic, evolutionary optimization algorithm NSGA-II [10]. The algorithm combines the ability to use the non-linear simulation as an objective function with the capability of obtaining multiple, non-dominated Pareto fronts. It further assures a good variation of results, using a crowding distance criterion. Previous optimizations showed that the maximum engine torque is a sensitive parameter and including it in the optimization can result in distorted or non-viable results; thus, the engine torque gradually increases for three discrete configurations. To exclude non-viable results, the solution space is constrained (Table II). The constraints for the two battery types result in physical differences [11], while the constrained overall gear ratio ensures that the engine speed does not drop below the idle speed when driving in the highest gear. The minimum climbing ability eliminates inefficient drivetrain configurations.

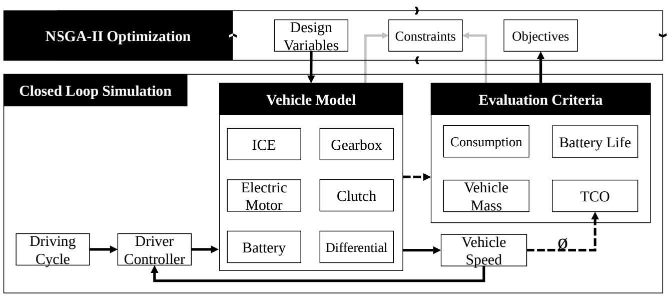

Figure 2. Forward simulation and optimization

TABLE II: CONSTRAINTS FOR MOP

Constraint		Value
Peak Charge (C-Rate)	Cylindrical	< 13
	Pouch	< 15
Overall Gear Ratio		> 2.3
Climbing Ability		> 10 %

III. PARAMETRIC COST AND MASS MODEL

The performance variation of the battery pack, the electric engine, the power electronics and the gearbox setup leads to a generic modelling of the components. Therefore, mass and cost models are derived and implemented in the vehicle model simulation. Depending on the setup of the design variables from Table I, the mass of the vehicle and the purchase costs of the hybrid-electric drive system are calculated for each individual in the optimization. The TCO includes the purchase price and the operating costs [12].

A. Battery Pack

A parametric battery cost model is used to calculate the necessary data for two different battery pack configurations. The first one is based on a cylindrical 21700 lithium ion cell; the second one is based on a pouch bag lithium ion cell. Both cells' designs use a modern NCM622 cell chemistry. Thus, the battery cost model is designed to calculate high energy cells; the fact that high power cells have to be designed is regarded through the reduction of the coating thickness of the active material (40 µm). Reducing the specific energy density of the active material according to [13] was no option because the limitations of the cost model.

The cost model itself is based on the Battery Performance and Cost Model (BatPaC) [14]. We added

- a raw material cost prediction until 2030
- production processes to also calculate cylindrical and prismatic cells, based on [15–17]
- prediction model for the technological development of the production processes based on [18]
- a quality prediction model also based on [18] to calculate reject and warranty costs
- fully parametric cell models based on [19] to calculate costs for different cell sizes
- future cell chemistries are added to portray the development of the lithium ion technology

The cost model calculations for the costs of the two differently regarded cells are based on a battery pack with 65 kWh to reach a necessary cell production yield in the fictitious cell production plant.

TABLE III SUMMARY OF BATTERY CALCULATION RESULTS

	21700 cylindrical cell	Pouch cell
Capacity	3.77 Ah	60 Ah
Nominal voltage	3.8 V	3.8 V
Mass	68 g	931 g
Extra mass → pack	125 kg	138 kg
Energy density based on a 65 kWh pack	151 Wh/kg	161 Wh/kg

To calculate the gravimetric energy density of the battery pack, the additional mass for housing, cooling, wiring etc. has to be calculated. Because of many existing possibilities to arrange cylindrical or pouch cells, the mean value for additional mass (of a best-case and worst-case battery pack design) was calculated. Table III summarizes the battery values used for the optimization. The aging of the battery pack is also taken into account and strongly influenced by the design variables total capacity and useable capacity. The vehicle modelling uses only the cyclic aging as the main criteria for heavy-duty battery pack applications [20]. The aging curve is based on the usable capacity and the number of charge and discharge cycles [21].

B. Electric Machine and Power Electronics

The relevant architecture of the electric machine for heavy-duty hybrid vehicles differs in two types. The first is an induction motor (IM). The IM consists of a fixed stator and a pivoted rotor. The windings for the three-phase are put in the stator with a 120° offset. The rotor is made of several cylindrically arranged conductors, which are short-circuited on both of their front ends [22]. The material costs for the IM are smaller in comparison to the permanent-magnet synchronous motor (PMSM). The stator of the PMSM has the same setup as used in the IM. The rotor consists of one stacked sheet metal package with radially mounted permanent magnets. The permanent magnets are made of rare earth metals. To prevent the magnets from being removed off the rotor at high speed, they are positioned with the high-quality adhesive materials, Kevlar or ceramic-binding [3]. Contrary to the high material costs of the PSM is the improved power density (Table IV).

The power electronics need to be adopted to the performance level of the battery and the electric machine. The integrated double-side cooling insulated-gate bipolar transistor (IGBT) power module (IPM) [23] is the state of the art. Double-side cooling is able to reduce the junction temperature rise of IGBTs in half, which means lower loss and higher reliability [24]. Table IV provides an overview of the assumed properties of the electric hybrid components.

TABLE IV: SPECIFIC COSTS AND MASSES OF HYBRID COMPONENTS [11, 12]

Component		Values	Unit
Battery pack	Pouch	176	€/kWh
		161	Wh/kg
	Cylindrical	210	€/kWh
		151	Wh/kg
EM	PMSM	12.9	€/kW
		2.0	kW/kg
	IM	10.3	€/kW
		0.9	kW/kg
Power Electronics IPM		3	€/kW
		10.8	kW/kg

C. Gearbox Design

Mass and cost functions for the gearbox design are based on a regression analysis from data sheets and component retail prices. The method derives the cost functions from an After-sales cost model that is based on the number of gears, the gear spread, overdrive and a dual clutch [25]. Table V displays the results

TABLE V: SPECIFIC COSTS AND MASS OF THE GEARBOX DESIGN

Component	Values	Unit
Gearbox (automatic)	17.4	€/kg
	$m_{Gearbox}$=75 ln($z_{Gears}T_{ICE}$)-510	kg
Gearbox (dual clutch)	19.9	€/kg
	$m_{Gearbox}$=125 ln($z_{Gears}T_{ICE}$)+923	kg

IV. OPTIMIZATION AND RESULTS

The results clearly show the downsizing potential of hybridization in long-haul applications. Table VI displays the vehicle parameter used in the optimization. The simulated vehicle is a semi-trailer tractor with a max. gross weight of 40 tons.

TABLE VI: VEHICLE PARAMETER [6, 10].

Parameter	Symbol	Unit	Value
Vehicle mass without drivetrain (Tractor + Trailer)	m_V	kg	10,623
Payload mass	m_P	kg	15,000
Frontal area	A	m²	10.3
Air drag coefficient	c_w	-	0.58
Rolling drag coefficient	c_{RR}	-	0.0052
Tire radius	r_{Tyre}	m	0.501
Standard rear axle ratio	i_{Axle}	-	2.846
Efficiency of axle drive	η_{Axle}	-	0.98
Average power auxiliary consumer	P_{Aux}	W	3,500
Efficiency gearbox	$\eta_{Gearbox}$	-	0.97
Efficiency gearbox direct drive	$\eta_{Gearbox\_direct}$	-	0.99

The TCO calculation assumes the use of the semi-trailer tractor unit for 6 years and includes the costs for replacing the aged battery pack. Assumptions of fuel and component costs for the simulation are put together in [12]. The overall TCO accumulates from the driver costs, the fuel costs, tolls, write-offs, transport/ vehicle insurance, etc. [12]. The quotient of the TCO and the overall mileage multiplied by the payload provides the first optimization objective, the TCO in Euros per ton kilometer. The transport efficiency is calculated from the fuel-consumption transferred into the CO_2-equivalent divided by the payload. It is a clear indicator for the fuel efficiency of the powertrain configuration. The last optimization objective is the elasticity of the drivetrain measured in time needed to accelerate from 60 to 80 km/h on flat ground. This criterion is necessary to generate robust drivetrain setups. It indicates the performance of the powertrain in the most frequent velocity zone in long-haul applications. The drivetrain topologies are optimized after 150 generations with 256 individuals. Fig. 3 displays the improvement ratio criterion (IR) for the evolutionary optimization algorithm [26]. The IR calculates the number of individuals that belong to the pareto front P_t and compares them with the fitness of the pareto front individuals from one generation before P_{t-1}. The mean clearly shows a convergence between 140 and 150 generations around 9 to 10 % of improvement. The improvement ratio is no indicator for a quantitative improvement, as it only shows the convergence.

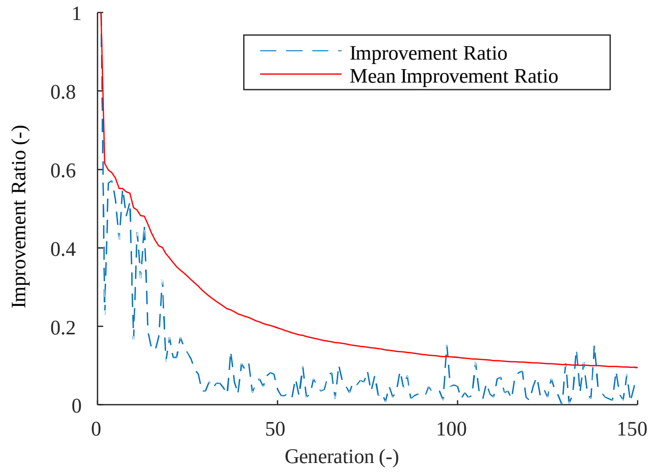

Figure 3. Convergence of the NSGA-II after 150 generations of optimization

Fig. 4 shows the quantitative pareto optimal solutions for the three discrete hybrid configurations separated by the discrete engine power levels (P_{ICE}).

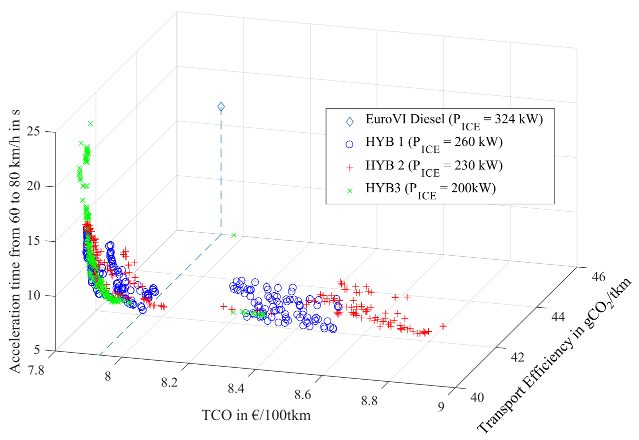

Figure 4. Pareto optimal solutions of the hybrid configurations with discrete engine power levels in the 150th generation of optimization

Compared to a standard Diesel engine with 324 kW power (lozenge and dashed line), the three hybrid configurations outperform in all of the optimization objectives. A closer look shows a cost reduction of 1.5 % with a simultaneous improvement of the transport efficiency of 9.9 to 10.7 % and an increased elasticity from 60 to 80 km/h of 9.5 to 19.5 %.

TABLE VII: Component Design and Optimum Powertrain Configuration

Configuration	**HYB1**	**HYB2**	**HYB3**
Hybrid Configuration			
Nominal System voltage		650 V	
Powertrain Configuration			
Engine		Diesel	
Maximum Power (P_{ICE})	260 kW	230 kW	200 kW
Maximum Torque (T_{ICE})	1700 Nm	1500 Nm	1300 Nm
Engine weight	800 kg	730 kg	655 kg
Results of the Optimum Individuals			
TCO in €/100tkm	7.81	7.82	7.83
Transport Efficiency in gCO_2/tkm	41.48	41.39	41.05
Elasticity from 60 to 80 km/h in s	13.44	13.69	15.13
Optimized Electric Drive System			
Electric motor	IM	PMSM	IM
Nominal power	145 kW	143 kW	152 kW
Electric torque	1258 Nm	1077 Nm	1200 Nm
Transition speed	1100 min^{-1}	1264 min^{-1}	1206 min^{-1}
Motor and controller weight	172 kg	83 kg	181 kg
Battery system	Pouch	Pouch	Pouch
Total capacity	37.4 kWh	39.9 kWh	43.8 kWh
Depth of Discharge	17.4 %	16.5 %	15.2 %
Battery weight	232 kg	245 kg	266 kg
Optimized Gearbox			
Gear spread	11.63	15.14	10.77
Number of Gears	8	10	8
Overdrive	False	False	False
Dual clutch	False	False	False
Rear axle ratio	2.799	2.906	2.8226
Gearbox weight	265 kg	259 kg	203 kg

TABLE VIII: RESULTS OF THE EURO VI DIESEL TRUCK [6]

Powertrain Configuration of the Euro VI Diesel Truck	
Engine	Diesel
Maximum Power (P_{ICE})	324 kW
Maximum Torque (T_{ICE})	2100 Nm
Engine weight	1011 kg
Gearbox Setup of the EuroVI Diesel Truck	
Gear spread	15.86
Number of Gears	12
Overdrive	False
Dual clutch	False
Rear axle ratio	2.846
Gearbox weight	391 kg
Results of the Euro VI Diesel Truck	
TCO	7.93 €/100tkm
Transport Efficiency	45.99 gCO_2/tkm
Elasticity from 60 to 80 km/h	16.7 s

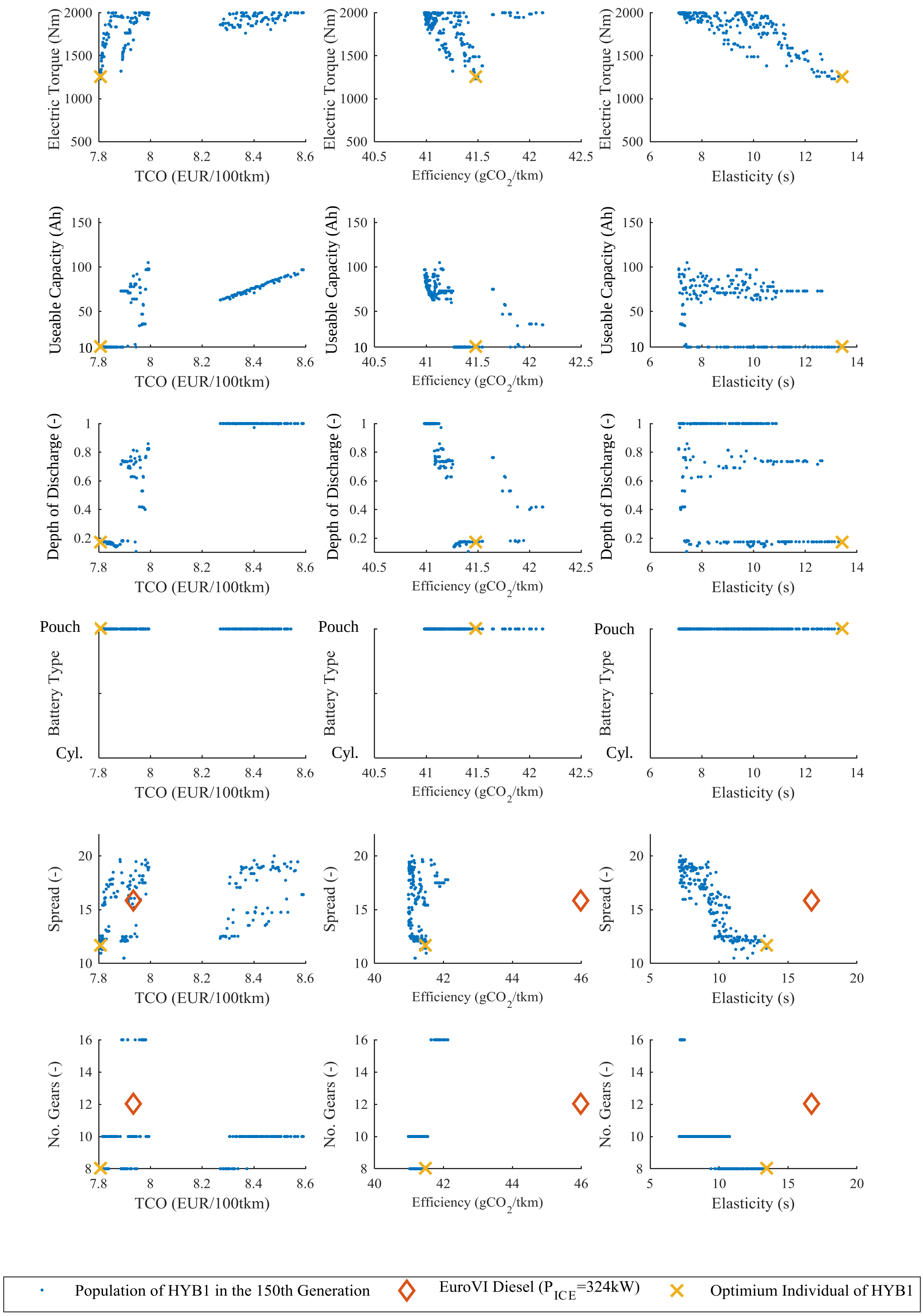

Figure 5. Optimization Results of HYB1

The HYB1 configuration achieves the best results according to the optimization objectives TCO and elasticity. Fig. 5 gives an overview of the most influential design parameters.

V. CONCLUSION AND OUTLOOK

In a series of cases (HYB1 and HYB3), the IM electric machine achieves the best results because of the lower costs. The factor is around 0.8 in comparison to the PSM machine. Nevertheless the choice of the electric machine is a contradiction between high power density (PMSM) and low costs (IM). As a consequence of the given customer requirements, the costs decrease, which directly affects the optimization objective TCO is more sensitive than the fuel savings due to lower mass. Additionally the higher efficiency of the IM at high speed meets the requirements of the simulated driving cycle with an average speed of 73 km/h. The analysis of the design variables in the last generation of the HYB1 configuration shows, the most influential parameter on the objectives is the maximum useable capacity of the battery system. One conclusion of this effect is that the useable capacity is an appropriate lever to provide a maximum lifetime of the battery pack, which is the most expensive component in the drive system. It is necessary to optimize the usable capacity before comparing the TCO with diesel trucks. The maximum electric torque defines the boundaries of transport efficiency. Several lines of evidence (HYB1, HYB2 and HYB3) demonstrate the advantage of the regarded pouch battery system in comparison to the cylindrical system. The optimum choice between the two cell types depends on the best-cost approximation of the battery pack. The gearbox spread and the number of gears are showing a clear optimization potential for hybrid vehicles with downsized engines. One reason is the starting support through the electric torque. This leads to the possibility of a smaller spread and less gears, still providing enough starting torque of the drive system. Another result is the fact that the HYB3 drivetrain configuration achieves similar results to those of HYB1 and HYB2 in regard to transport efficiency, TCO and elasticity, although the engine size is smaller. Altogether, the engine downsizing leads to improved transport efficiency with lower CO_2 emissions compared to the standard Euro VI engine. An optimum choice of the electric components, such as an electric machine and battery system, clearly improves the applicability of hybrid vehicles in the long-haul industry to meet customer requirements.

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