35th International Electric Vehicle Symposium and Exhibition (EVS35)
Oslo, Norway, June 11-15, 2022

Concurrent Powertrain Design for a Family of Electric Vehicles

Maurizio Clemente[1], Mauro Salazar[1], Theo Hofman[1]
[1]Eindhoven University of Technology, De Rondom 70, 5612 AP Eindhoven, The Netherlands
m.clemente@tue.nl

Executive Summary

Electric vehicles still account for a small share of the total amount of cars on the road. One of the major issues preventing a larger uptake is their higher upfront cost compared to petrol cars. We aim to address this issue by investigating a module-based product-family approach to take full advantage of economy-of-scale strategies, reducing research, development, and production costs of electric vehicles. This paper instantiates a concurrent design optimization framework, whereby different vehicle types share multiple modular powertrain components, whose size is jointly optimized to minimize the overall operational costs instead of being individually tailored. In particular, we focus on sizing battery and electric motors for a family of vehicles equipped with in-wheel motors. First, we identify a convex model of the powertrain, capturing the impact of modules' sizing and multiplicity on the mechanical power demand and the energy consumption of the vehicles. Second, we frame the concurrent powertrain design and operation problem as a second-order conic program that can be efficiently solved with global optimality guarantees. Finally, we showcase our framework for a family of two different vehicles: a city car and a compact car. Our results show that concurrently optimizing shared components increases the operational costs by less than 3% compared to individually tailoring them to each vehicle, a value that would be largely overshadowed by the benefits stemming from using the same components for the entire product family.

Keywords: BEV (battery electric vehicle), Convex Optimization, Battery & EM model, Cost, Design Methodologies

1 Introduction

The transition to sustainable energy and mobility is not progressing fast enough to meet objectives set by world leaders [1]. Electric Vehicles (EVs) hold the potential to play a leading role in the future of transportation, keeping cities less polluted and significantly reducing CO_2 emissions [2]. Nevertheless, their higher upfront cost compared to conventional petrol vehicles could slow down the transition to cleaner mobility. In order to address this issue, we leverage product-family and economy-of-scale strategies to develop and produce vehicles at a lower cost by designing their components in a modular fashion. Each vehicle type contains one or multiple identical modules, jointly optimized to minimize the operational cost of the whole family, accounting for the changing module's size as well as multiplicity (Fig. 1). This paper presents a convex design optimization framework with the scope of concurrently sizing battery and electric motors (EMs) for a family of battery electric vehicles (BEV) equipped with in-wheel motors.

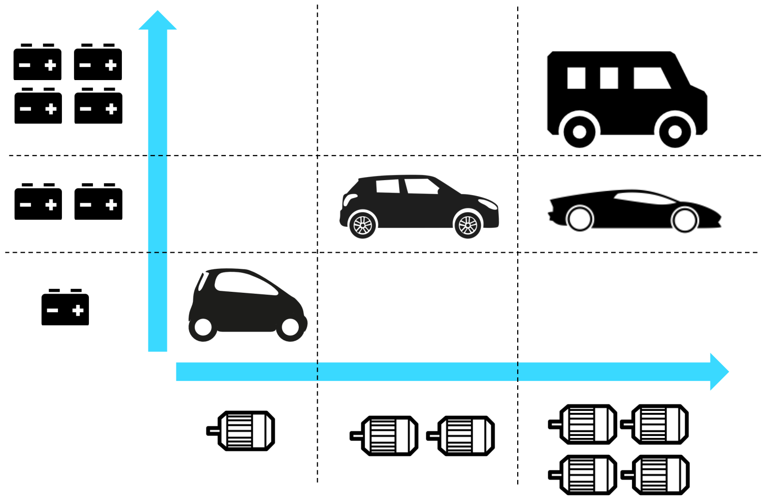

Figure 1: Product family generated by the combination of two powertrain subsystems: electric motor and battery.

Literature Review: This paper pertains to two main research lines: powertrain and product-family design. Powertrain design for single vehicles has been extensively studied, leading to a variety of models [3] and optimization strategies [4]. For instance, [5] jointly design powertrain and controls to minimize the energy consumption, while [6] and [7] maximize performances. However, to the best of the authors' knowledge, these methods do not account for multiple vehicles at the same time. The second research stream concerns product-family and platform design. These methodologies have been widely studied and employed by industrial players due to their substantial benefits, proving to be effective in reducing components' costs and providing operational advantages in part sourcing, manufacturing, and quality control [8]. They also foster the development and upgrade of differentiated products efficiently, increase flexibility and responsiveness in manufacturing processes [9], and generate enormous savings in research, testing, interface design, and integration [10]. Finally, producing or buying components in larger quantities triggers further saving, enabling economy-of-scale strategies. Traditionally, in a module-based product family, new products are instantiated by adding, substituting, and removing one or more functional modules [11], such as the battery pack or the electric motor. This strategy is called *horizontal leveraging* and concerns more products sharing the same modules for different applications. Conversely, *vertical leveraging* involves scaling components to attack different market niches. A visual representation of these strategies is shown in Fig. 2. Nevertheless, the combined application of module-based product family concepts and vehicles optimization has not been studied extensively. A thorough search of the relevant literature yielded only one related study. [12, 13] used optimization for making commonality decisions while controlling individual performance in a family of cars and developed a sensitivity-based commonality strategy for family products of mild variation. Yet, their application concerns only automotive body structures. In conclusion, to the best of the authors' knowledge, there still appears to be a research gap regarding the application of product-family strategies to powertrain design optimization.

1.1 Contribution

In this paper, we propose to bridge this gap by applying modularity and standardization to a family of battery electric vehicles. We introduce a framework consisting in designing optimal single-sized modules, specifically an in-wheel EM and a battery, for a whole family of vehicles. Instead of individual scaling, we employ multiple copies of the same module to reach higher power and battery energy. The modules' size is determined by using a convex optimization approach, taking into account the impact of changing components' sizes and multiplicity to find the optimal compromise between a vehicle-tailored design that would minimize energy consumption, and the requirement to produce different kinds of vehicles to serve customer needs. We refer to this methodology as "Concurrent Design Optimization" due to the fact that we perform a joint optimization of multiple powertrain components, considering every vehicle in the family simultaneously.

Organization: The remainder of this paper is structured as follows: Section 2 presents the vehicles' model, Section 3 formulates the optimization problem, and Section 4 presents the numerical results. Finally, the conclusions are discussed in Section 5, along with an outlook on future research.

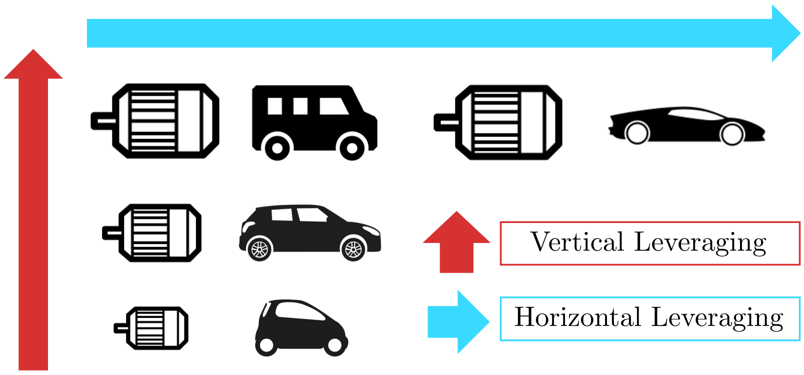

Figure 2: Module-leveraging strategies in a family of vehicles.

2 Model

This section introduces the convex model of the vehicles that we employ in our framework (Fig. 3). In line with common practices, we used a quasi-static approximation [14] for each of the main components that make up the powertrain: EMs and battery. In Section 2.1 we introduce and explain the meaning and use of scaling and multiplicity factors. Section 2.2 sets forth the longitudinal vehicle dynamics, and Section 2.3 gives insights on the vehicles' mass model, taking into account the changing components' size in the optimization. Section 2.4 focuses on the electric motor, and Section 2.5 on the battery modelling. Finally, Section 2.6 shows the model we used to estimate the operational costs. For the sake of simplicity, we drop dependence on time t whenever it is clear from the context.

2.1 Scaling and Multiplicity Factors

We construct our model starting from the reference motor and battery that we used for the identification of parameters and we assume that quantities scale linearly with the components' size. For this reason, we introduce the scaling factors

$$S_\mathrm{m} = \frac{P_\mathrm{m,max}}{\overline{P}_\mathrm{m,max}},$$

$$S_\mathrm{b} = \frac{E_\mathrm{b,max}}{\overline{E}_\mathrm{b,max}},$$

where S_m is the motor scaling factor, $P_\mathrm{m,max}$ and $\overline{P}_\mathrm{m,max}$ are the maximum output power of the motor and of the reference motor, respectively. Similarly, S_b is the battery scaling factor, while $E_\mathrm{b,max}$ and $\overline{E}_\mathrm{b,max}$ are the maximum energy of the battery and of the reference battery. Nevertheless, this approximation is only valid in the range of scales

$$S_\mathrm{m} \in [S_\mathrm{m,min}, S_\mathrm{m,max}] \subseteq \mathbb{R}_+ \tag{1}$$

$$S_\mathrm{b} \in [S_\mathrm{b,min}, S_\mathrm{b,max}] \subseteq \mathbb{R}_+. \tag{2}$$

Moreover, we account for the components' multiplicity in the powertrain by introducing the motor and battery multiplicity: $N_{\mathrm{m},i} \in \mathbb{N}_+$ and $N_{\mathrm{b},i} \in \mathbb{N}_+$, with the subscript i indicating that the quantity differs from one vehicle type to the other. These pre-defined coefficients represent the number of module units present in the powertrain.

2.2 Longitudinal Vehicle Dynamics

In order to compute the power requirement of the vehicles, we consider a given driving cycle consisting of an exogenous longitudinal speed and acceleration trajectory: $v(t)$ and $a(t)$. For each vehicle, the required power P_req depends on aerodynamic drag, rolling friction, gravitational force, and inertial force.

$$P_{\mathrm{req},i} = m_i \cdot v \cdot (c_{\mathrm{r},i} \cdot g \cdot \cos(\theta) + g \cdot \sin(\theta) + a) + \frac{1}{2} \cdot \rho \cdot c_{\mathrm{d},i} \cdot A_{\mathrm{f},i} \cdot v^3, \tag{3}$$

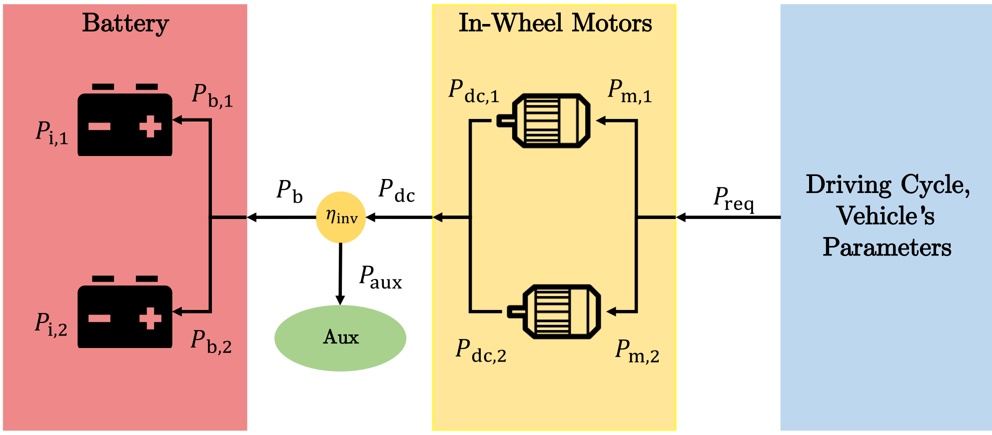

Figure 3: Block diagram of a vehicle with two in-wheel motor and two battery modules.

where m_i is the total mass of each vehicle subject to optimization, $c_{\mathrm{r},i}$ the rolling friction coefficient, g the gravitational acceleration, ρ the density of the air, θ the road inclination, $c_{\mathrm{d},i}$ the aerodynamic drag coefficient and $A_{\mathrm{f},i}$ the frontal area.

2.3 Mass

For each vehicle we compute the total mass as the sum of glider (vehicle without powertrain), battery, and motor mass. While the glider mass $m_{0,i}$ varies from one type of vehicle to another, motor and battery mass are computed by scaling the reference components mass $\overline{m}_{\mathrm{m}}$ and $\overline{m}_{\mathrm{b}}$

$$m_i = m_{0,i} + \overline{m}_{\mathrm{b}} \cdot S_{\mathrm{b}} + \overline{m}_{\mathrm{m}} \cdot S_{\mathrm{m}}. \tag{4}$$

2.4 Electric Motor

In this study, we consider in-wheel electric motors as movers. Since there is a direct mechanical link between motors and wheels, assuming that each motor handles an equal amount of power, the output power of every motor $P_{\mathrm{m},i}$ can be computed as

$$P_{\mathrm{m},i} = \begin{cases} \frac{P_{\mathrm{req},i}}{N_{\mathrm{m},i}} & \text{if } P_{\mathrm{req},i} \geq 0 \\ r_{\mathrm{b},i} \cdot \frac{P_{\mathrm{req},i}}{N_{\mathrm{m},i}} & \text{if } P_{\mathrm{req},i} < 0 \end{cases}. \tag{5}$$

In case of negative power requirement, we introduce a regenerative braking fraction that the electric motor can exert via the rear axle of the vehicle without destabilizing the vehicle $r_{\mathrm{b},i}$. Moreover, each motor is bounded to not exceed its operational limits $P_{\mathrm{m,min}}$ and $P_{\mathrm{m,max}}$, computed by scaling the reference values:

$$P_{\mathrm{m},i} \in \left[\overline{P}_{\mathrm{m,min}}, \overline{P}_{\mathrm{m,max}}\right] \cdot S_{\mathrm{m}}. \tag{6}$$

Motor losses $P_{\mathrm{m,loss}}$ are computed by scaling a second-order polynomial approximation of the reference motor losses $\overline{P}_{\mathrm{m,loss}}$ derived from the quadratic approach used by [15]:

$$\overline{P}_{\mathrm{m,loss}} = P_0(\omega) + \beta(\omega) \cdot \overline{P}_{\mathrm{m}} + \alpha(\omega) \cdot \overline{P}^2_{\mathrm{m}},$$

where the parameters $P_0(\omega)$, $\beta(\omega)$, and $\alpha(\omega)$ are dependent on the motor speed ω and subject to identification. Considering the scaling factor S_{m}, the motor losses become

$$P_{\mathrm{m,loss},i} = \left(P_0(\omega) + \beta(\omega) \cdot \frac{P_{\mathrm{m},i}}{S_{\mathrm{m}}} + \alpha(\omega) \cdot \frac{P^2_{\mathrm{m},i}}{S^2_{\mathrm{m}}} \right) \cdot S_{\mathrm{m}},$$

yielding

$$P_{\mathrm{m,loss},i} = P_0(\omega) \cdot S_{\mathrm{m}} + \beta(\omega) \cdot P_{\mathrm{m},i} + \alpha(\omega) \cdot \frac{P_{\mathrm{m},i}^2}{S_{\mathrm{m}}}.$$

Consequently, we can write the total input power $P_{\mathrm{dc},i}$ as

$$P_{\mathrm{dc},i} = N_{\mathrm{m},i} \left(P_{\mathrm{m},i} + P_{\mathrm{m,loss},i}\right) = N_{\mathrm{m},i} \left(P_{\mathrm{m},i} + P_0(\omega) \cdot S_{\mathrm{m}} + \beta(\omega) \cdot P_{\mathrm{m},i} + \alpha(\omega) \cdot \frac{P_{\mathrm{m},i}^2}{S_{\mathrm{m}}}\right). \quad (7)$$

This approximation is particularly useful in this context since it allows to retain accuracy and complexity without losing convexity. In fact, (7) can be relaxed to a convex second-order conic constraint, as it will be shown in Section 3.1.

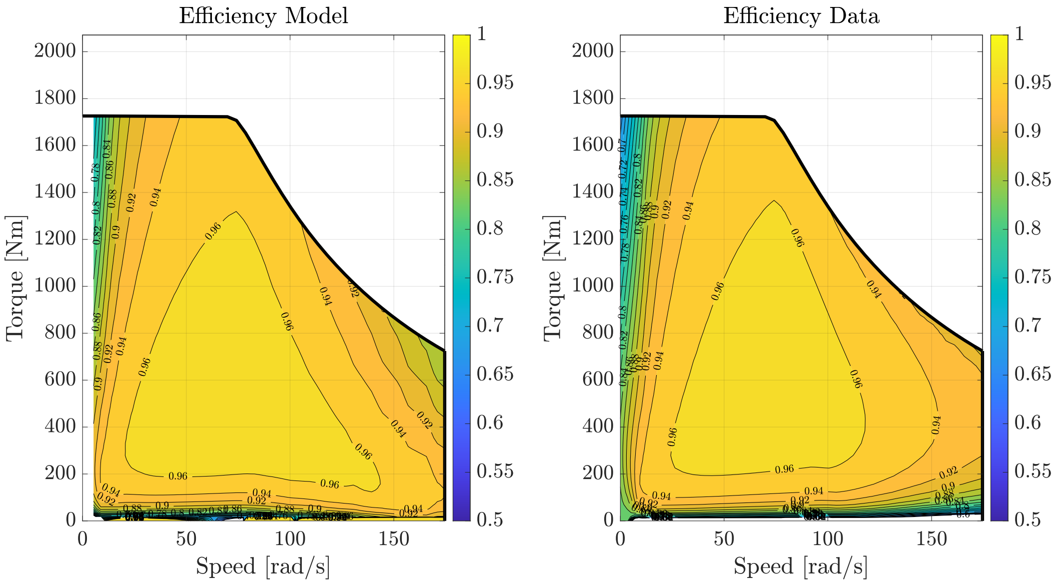

Figure 4: Electric motor efficiency map computed using the model (left) compared with data (right). We mirror the efficiency for negative torques.

2.5 Battery

The power output of the batteries $P_{\mathrm{b},i}$ is computed from the total motors' input power $P_{\mathrm{dc},i}$, taking into account the inverter efficiency η_{inv}, the battery modules' multiplicity $N_{\mathrm{b},i}$, and auxiliaries consumption $P_{\mathrm{aux},i}$ as follows:

$$P_{\mathrm{b},i} = \begin{cases} \frac{1}{N_{\mathrm{b},i}} \cdot \left(\frac{P_{\mathrm{dc},i}}{\eta_{\mathrm{inv}}} + P_{\mathrm{aux},i}\right) & \text{if } P_{\mathrm{dc},i} \geq 0 \\ \frac{1}{N_{\mathrm{b},i}} \cdot \left(\eta_{\mathrm{inv}} \cdot P_{\mathrm{dc},i} + P_{\mathrm{aux},i}\right) & \text{if } P_{\mathrm{dc},i} < 0 \end{cases}. \quad (8)$$

Assuming that every battery module supplies an equal amount of output power, we approximate the internal losses $P_{\mathrm{loss,b},i}$ of each module with a quadratic function of the output power:

$$P_{\mathrm{b,loss},i} = \frac{P_{\mathrm{b},i}^2}{P_{\mathrm{sc},i}},$$

where the coefficient $P_{\mathrm{sc},i}$ is a measure of the efficiency of the battery. It has the dimensions of a power, and it is called "Short Circuit Power" in reference to the power that would be released short-circuiting the battery. In turn, $P_{\mathrm{sc},i}$ depends on the battery energy $E_{\mathrm{b},i}$ and the battery size S_{b} and, in line with [15], can be expressed as

$$P_{\mathrm{sc},i} = \min_{k} \left\{ a_k \cdot E_{\mathrm{b},i} + b_k \cdot S_{\mathrm{b}} \right\}, \tag{9}$$

where a_k and b_k are the linear and constant coefficients, respectively, identified from a piecewise approximation of the short circuit power curve as a function of the reference battery energy. Hence, for each battery module, the internal power $P_{\mathrm{i},i}$ can be expressed as

$$P_{\mathrm{i},i} = P_{\mathrm{b},i} + \frac{P_{\mathrm{b},i}^2}{P_{\mathrm{sc},i}}. \tag{10}$$

The internal power induces a variation of the battery energy $E_{\mathrm{b},i}$ as

$$\frac{\mathrm{d}E_{\mathrm{b},i}}{\mathrm{d}t} = -P_{\mathrm{i},i}. \tag{11}$$

The energy consumption of each battery module is the difference between the energy at the beginning of the driving cycle $E_{\mathrm{b},i}(0)$ and the energy remaining at its end $E_{\mathrm{b},i}(T)$. In order to get the overall energy consumption in the drive cycle $E_{\mathrm{cons},i}$ we need to include the multiplicity factor:

$$E_{\mathrm{cons},i} = N_{\mathrm{b},i} \cdot \left(E_{\mathrm{b},i}(0) - E_{\mathrm{b},i}(T) \right).$$

However, we consider each battery module's energy to stay within operational limits, leading to

$$E_{\mathrm{b},i} \in \left[\overline{E}_{\mathrm{b,max}} \cdot \xi_{\mathrm{min}}, \overline{E}_{\mathrm{b,max}} \cdot \xi_{\mathrm{max}} \right] \cdot S_{\mathrm{m}}, \tag{12}$$

where ξ is the state of charge of a battery module and $\overline{E}_{\mathrm{b,max}}$ is the maximum energy capacity of the reference battery. To represent an average battery use during the cycle, we impose that the average between the energy at the beginning of the cycle $E_{\mathrm{b},i}(0)$ and at the end $E_{\mathrm{b},i}(T)$ must equal the mean battery energy level:

$$E_{\mathrm{b},i}(0) + E_{\mathrm{b},i}(T) = S_{\mathrm{b}} \left(\xi_{\mathrm{max}} + \xi_{\mathrm{min}} \right) \cdot \overline{E}_{\mathrm{b,max}}. \tag{13}$$

2.6 Operational Costs

The costs of operation for each vehicle type J_i is estimated considering the overall energy consumption during a lifetime of N_{y} years:

$$J_i = C_{\mathrm{e}} \cdot E_{\mathrm{cons},i} \cdot \frac{N_{\mathrm{y}} \cdot D_{\mathrm{year}}}{D_{\mathrm{cycle}}}, \tag{14}$$

where D_{cycle} and D_{year} are the distance driven during the cycle and during one year, respectively, whereas C_{e} is the mean cost of electric energy. We neglect maintenance costs as their influence is two orders of magnitude smaller [16].

3 Problem formulation

In this section we formulate the concurrent design optimization as a convex second-order conic problem. Section 3.1 shows the lossless relaxation of non-convex constraints, while Section 3.2 introduces performance constraints and Section 3.3 recalls the objective function before formulating the concurrent powertrain design problem as a second-order conic program. Finally, in Section 3.4 we discuss the assumptions and limitations of our approach.

3.1 Constraints Relaxation

In order for the problem to be framed in a convex fashion, we need to relax constraints (5), (7), (8), (9), and (10). Since our goal is to minimize the TCO, and consequently the energy consumption, these constraints will always hold with equality, because it is suboptimal to assume any higher value than the strictly necessary. For the sake of brevity, we refrain from proving that these relaxations are lossless, as the reason lies in the same principle. Therefore, (5) and (8) become

$$P_{\mathrm{m},i} \geq \frac{P_{\mathrm{req},i}}{N_{\mathrm{m},i}} \tag{15}$$

$$P_{\mathrm{m},i} \geq r_{\mathrm{b},i} \cdot \frac{P_{\mathrm{req},i}}{N_{\mathrm{m},i}} \tag{16}$$

$$P_{\mathrm{b},i} \geq \frac{1}{\eta_{\mathrm{inv}}} \cdot P_{\mathrm{dc},i} + P_{\mathrm{aux},i} \tag{17}$$

$$P_{\mathrm{b},i} \geq \eta_{\mathrm{inv}} \cdot P_{\mathrm{dc},i} + P_{\mathrm{aux},i}, \tag{18}$$

whilst (7) and (10) can be expressed as second-order conic constraints [17] as

$$\left(\frac{P_{\mathrm{dc},i}}{N_{\mathrm{m},i}} - P_{\mathrm{m},i} - S_{\mathrm{m}} \cdot P_0(\omega) + \beta(\omega) \cdot P_{\mathrm{m},i}\right) + \frac{S_{\mathrm{m}}}{\alpha(\omega)} \geq \left\| \begin{matrix} 2 \cdot P_{\mathrm{m},i} \\ \left(\frac{P_{\mathrm{dc},i}}{N_{\mathrm{m},i}} - P_{\mathrm{m},i} - S_{\mathrm{m}} \cdot P_0(\omega) + \beta(\omega) \cdot P_{\mathrm{m},i}\right) - \frac{S_{\mathrm{m}}}{\alpha(\omega)} \end{matrix} \right\|_2, \tag{19}$$

$$(P_{\mathrm{i},i} - P_{\mathrm{b},i}) + P_{\mathrm{sc},i} \geq \left\| \begin{matrix} 2 \cdot P_{\mathrm{b},i} \\ (P_{\mathrm{i},i} - P_{\mathrm{b},i}) - P_{\mathrm{sc},i} \end{matrix} \right\|_2. \tag{20}$$

Finally, (9) is relaxed to a set of affine inequalities:

$$P_{\mathrm{sc},i} \leq \min_k \left\{a_k \cdot E_{\mathrm{b},i} + b_k \cdot S_{\mathrm{b}}\right\}. \tag{21}$$

3.2 Performance Constraints

In addition to constraints on the powertrain, we included performance constraints in contemplation of comparisons with vehicles on the market. Thus, for each vehicle type we find, in order: acceleration time, top speed, power gradability, torque gradability, and range constraints

$$N_{\mathrm{m},i} \cdot S_{\mathrm{m}} \cdot t_{\mathrm{acc}} \leq \frac{\omega_{\mathrm{r}} \cdot r_{\mathrm{w},i}^2 \cdot m_i}{\overline{T}_{\mathrm{m,max}}} + \frac{m_i \cdot \left(v_{\mathrm{f}}^2 + \omega_{\mathrm{r}}^2 \cdot r_{\mathrm{w},i}^2\right)}{2 \cdot \overline{P}_{\mathrm{m,max}}} \tag{22}$$

$$N_{\mathrm{m},i} \cdot S_{\mathrm{m}} \cdot \overline{P}_{\mathrm{m,max}} \geq \frac{1}{2} \cdot \rho \cdot c_{\mathrm{d},i} \cdot A_{\mathrm{f},i} \cdot v_{\mathrm{max}}^3 \tag{23}$$

$$N_{\mathrm{m},i} \cdot S_{\mathrm{m}} \cdot \overline{P}_{\mathrm{m,max}} \geq m_i \cdot g \cdot v_{\mathrm{min}} \cdot \sin(\theta_{\mathrm{max}}) \tag{24}$$

$$N_{\mathrm{m},i} \cdot S_{\mathrm{m}} \cdot \overline{T}_{\mathrm{m,max}} \geq m_i \cdot g \cdot r_{\mathrm{w}} \cdot \sin(\theta_{\mathrm{max}}) \tag{25}$$

$$E_{\mathrm{b},i}(0) - E_{\mathrm{b},i}(T) \leq N_{\mathrm{b},i} \cdot S_{\mathrm{b}} \cdot (\xi_{\mathrm{max}} + \xi_{\mathrm{min}}) \cdot \overline{E}_{\mathrm{b,max}} \cdot \frac{D_{\mathrm{cycle}}}{D_{\mathrm{range}}}, \tag{26}$$

where t_{acc} is the maximum acceleration time from 0 to v_{f}, v_{max} the top speed, D_{range} the minimum range, v_{min} is the speed at which the vehicle shall be able to drive facing a slope of θ_{max}, and $\overline{T}_{\mathrm{m,max}}$ is the maximum reference torque. It can be computed from the maximum reference power of the motor and the rated speed ω_{r} as

$$\overline{T}_{\mathrm{m,max}} = \frac{\overline{P}_{\mathrm{m,max}}}{\omega_{\mathrm{r}}}.$$

3.3 Objective Function and Problem Formulation

As the objective of the concurrent powertrain design problem, we select the sum of operational costs of every vehicle in the fleet J_{tot}

$$J_{\mathrm{tot}} = \sum_{i=1}^{I} \left(N_{\mathrm{v},i} J_i \right).$$

We state the cost-optimal sizing problem as follows:

Problem 1 (**Concurrent Powertrain Design**). *Given a family of battery electric vehicles with a modular powertrain as shown in Fig. 3, the optimal components' sizes for the whole family are the solution of*

$$\begin{aligned} &\min J_{\mathrm{tot}} \\ &\textit{s.t.}\ \ \textit{Shared Constraints}\ (1), (2) \\ &\qquad \textit{Powertrain Constraints}\ (3),(4),(6),\ (11)\text{-}(21) \quad \forall i \\ &\qquad \textit{Performance Constraints}\ (22)\text{-}(26) \qquad \forall i \end{aligned}$$

This problem can be framed as a second-order conic program and can be rapidly solved to global optimality with standard algorithms.

3.4 Discussion

A few comments are in order. First, we scale the electric motor mass linearly as a function of the maximum power. Second, we scale the battery size only by acting on the number of cells in parallel, thus changing its energy without altering the battery voltage. These scaling methods are in line with high-level modelling approaches and optimal sizing design problems. In fact, if the size is between 50% and 200% of the reference, the approximations are quite accurate [18]. Finally, it is important to underline that, in our framework, the scaling factors are optimization variables, while the modules multiplicity are given parameters. This limitation could be readily overcome by solving a sequence of problems in a combinatorial manner, yet this is beyond the scope of the present paper.

4 Results

In this section we show the potential of our methodology with a numerical case study for a family composed of two vehicles of different types: a city car and a compact car (with $N_{\mathrm{v},1} = 1$, and $N_{\mathrm{v},2} = 1$). In our analysis, we consider the Class 3 Worldwide harmonized Light-duty vehicles Test Cycle (WLTC) for the speed and acceleration trajectories, whilst vehicles and simulation parameters are provided in Tables 1 and 3. We discretize Problem 1 using the Euler forward method with a sampling time of 1 s. Thereafter, we parse it with YALMIP [19] and solve it to global optimality with MOSEK [20], in approximately 2 s.

Our results show that sizing powertrain components concurrently only causes an average increase of the operation costs of 2.76% for the family, compared to the individual vehicle-tailored optimization. It is expected that this value will be largely outperformed by the benefits derived from using a single component shared by the entire product family [8]. The vehicle-specific increment of operational costs is shown in detail in Fig. 5. Both approaches obtain similar results for the small city car, with a limited variation of 0.41%, whilst the larger compact car shows a difference of 5.10%. This dissimilarity can be ascribed to the fact that a shared module may be oversized for one of the vehicles to serve the whole fleet at best. In particular, we find that the compact car carries a larger battery than required due to its minor energy consumption compared to the city car. Nonetheless, for both vehicles, the increase of operational cost is accompanied by an improvement in performance, such as a shorter acceleration time, an extended range, or a higher top speed, as shown in Tables 4 and 5.

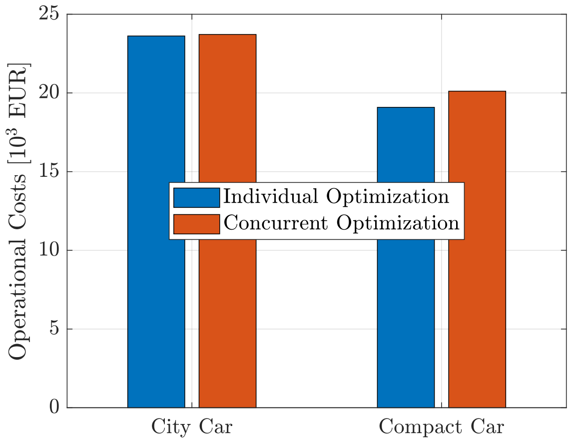

Figure 5: Operational cost of two vehicles sharing powertrain modules: A city car (left) and a compact car (right). The blue and the orange bars indicate the results attained with individual and concurrent optimization.

Table 1: Vehicles Parameters

Symbol	**City Car**	**Compact Car**	**Unit**
A_f	2.38	2.43	m^2
r_w	0.3498	0.3594	m
c_d	0.29	0.23	–
c_r	0.0174	0.008	–
η_inv	0.96	0.96	–
r_b	0.7	0.6	–
m_0	850	1250	kg
$\overline{m}_\mathrm{b}$	138.6		kg
$\overline{m}_\mathrm{m}$	81.6		kg

5 Conclusions

This paper explored product-family design for electric powertrain applications. We devised a concurrent optimization framework to design powertrain components shared within a family of electric vehicles equipped with in-wheel motors. Our framework can jointly optimize the operation of the individual vehicles and the size of electric motors and battery, accounting for their multiplicity within each powertrain, without requiring time-consuming iterative methods. Conversely, the convex problem format enabled us to rapidly compute the globally optimal solution with off-the-shelf second-order conic programming algorithms. Focusing on a two-vehicle family consisting of an urban car and a compact car, our case-study revealed the potential of EVs: Compared to the case where the components are individually tailored to each vehicle, concurrently designing shared components would increase the operational costs by less than 3%.

This work opens the field for the following extensions: First, our initial results prompt a detailed economical analysis of the benefits of product-family design for EVs in terms of horizontal leveraging and economy-of-scale. Second, we would like to study different powertrain architectures and transmission technologies. Finally, we are interested in jointly optimizing the multiplicity of component units within each vehicle.

Table 2: Minimum Performance Parameters

Symbol	Value	Unit
t_{acc}	15	s
v_{f}	100	km/h
$v_{\max}$	130	km/h
$v_{\min}$	10	km/h
$\theta_{\max}$	10	deg
D_{range}	300	km

Table 3: Simulation Parameters

Symbol	City Car	Compact Car	Unit
$SOC_{\min}$	0.2	0.2	–
$SOC_{\max}$	0.8	0.8	–
N_{m}	2	2	–
N_{b}	1	1	–
P_{aux}	500	500	W
D_{year}	20000	20000	km
N_{y}	5	5	years
C_{e}	0.36	0.36	EUR/MJ

Table 4: City car mass and performance

Performance	Individual Opt.	Concurrent Opt.
Mass	1431 kg	1448 kg
Range	300 km	300 km
Acceleration Time	14.5 s	11 s
Top Speed	198 km/h	217 km/h
Energy Usage	0.65 MJ/km	0.65 MJ/km

Table 5: Compact car mass and performance

Performance	Individual Opt.	Concurrent Opt.
Mass	1739 kg	1848 kg
Range	300 km	353 km
Acceleration Time	14 s	14 s
Top Speed	228 km/h	233 km/h
Energy Usage	0.53 MJ/km	0.56 MJ/km

Acknowledgments

We wish to thank Dr. I. New, Ir. O.J.T. Borsboom, Ir. F. Paparella, and Ir. C.A.J. Hanselaar for proofreading this paper. This publication is part of the project NEON with project number 17628 of the research program Crossover which is (partly) financed by the Dutch Research Council (NWO).

References

[1] UNEP and D. Partnership, "Emissions gap report 2021: The heat is on – a world of climate promises," United Nations Environment Programme and Technical University of Denmark, Tech. Rep., 2021.

[2] IEA, "Global ev outlook 2020," IEA, Paris, Tech. Rep., 2020.

[3] F. J. R. Verbruggen, V. Rangarajan, and T. Hofman, "Powertrain design optimization for a battery electric heavy-duty truck," in *American Control Conference*, 2019.

[4] E. Silvas, T. Hofman, N. Murgovski, P. Etman, and M. Steinbuch, "Review of optimization strategies for system-level design in hybrid electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 1, pp. 57–70, 2016.

[5] T. Hofman and M. Salazar, "Transmission ratio design for electric vehicles via analytical modeling and optimization," in *IEEE Vehicle Power and Propulsion Conference*, 2020.

[6] O. Borsboom, C. A. Fahdzyana, T. Hofman, and M. Salazar, "A convex optimization framework for minimum lap time design and control of electric race cars," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 9, pp. 8478–8489, 2021.

[7] M. Salazar, P. Duhr, C. Balerna, L. Arzilli, and C. H. Onder, "Minimum lap time control of hybrid electric race cars in qualifying scenarios," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 7296–7308, 2019.

[8] J. Jiao, T. Simpson, and Z. Siddique, "Product family design and platform-based product development: a state-of-the-art review," *Journal of Intelligent Manufacturing*, vol. 18, no. 1, pp. 5–29, 2007.

[9] D. Robertson and K. Ulrich, "Planning for product platforms," *The Wharton Annual*, vol. 39, no. 4, pp. 19–31, 1998.

[10] K. Otto, K. Hölttä-Otto, T. W. Simpson, D. Krause, S. Ripperda, and S. K. Moon, "Global views on modular design research: Linking alternative methods to support modular product family structure design," *ASME Journal of Mechanical Design*, vol. 138, no. 7, p. 071101, 2016.

[11] T. Simpson, Z. Siddique, and J. J., *Product Platform and Product Family Design Methods and Applications*, 1st ed. Springer US, 2006.

[12] R. Fellini, M. Kokkolaras, N. Michelena, P. Papalambros, K. Saitou, and A. Perez-Duarte, "A sensitivity-based commonality strategy for family products of mild variation, with application to automotive body structures," in *AIAA/ISSMO Symp. on Multidisciplinary Analysis and Optimization*, 2002.

[13] R. Fellini, M. Kokkolaras, and P. Y. Papalambros, "Platform selection under performance loss constraints in optimal design of product families," in *ASME Design Engineering Technical Conferences - Design Automation Conference*, 2002.

[14] L. Guzzella and A. Sciarretta, *Vehicle propulsion systems: Introduction to Modeling and Optimization*, 2nd ed. Springer Berlin Heidelberg, 2007.

[15] F. J. R. Verbruggen, M. Salazar, M. Pavone, and T. Hofman, "Joint design and control of electric vehicle propulsion systems," in *European Control Conference*, 2020.

[16] A. König, L. Nicoletti, D. Schröder, S. Wolff, A. Waclaw, and M. Lienkamp, "An overview of parameter and cost for battery electric vehicles," *World Electric Vehicle Journal*, vol. 12, no. 1, pp. 21–50, 2021.

[17] S. Ebbesen, M. Salazar, P. Elbert, C. Bussi, and C. H. Onder, "Time-optimal control strategies for a hybrid electric race car," *IEEE Transactions on Control Systems Technology*, vol. 26, no. 1, pp. 233–247, 2018.

[18] E. A. Grunditz and T. Thiringer, “Modelling and scaling procedure of a vehicle electric drive system,” Chalmers University of Technology, Tech. Rep., 2017.

[19] J. Löfberg, “YALMIP : A toolbox for modeling and optimization in MATLAB,” in *IEEE Int. Symp. on Computer Aided Control Systems Design*, 2004.

[20] M. ApS. (2017) MOSEK optimization software. Available at https://mosek.com/.

Presenter Biography

Maurizio Clemente is a Ph.D. student in the Control System Technology (CST) section at Eindhoven University of Technology, The Netherlands. He studied aerospace engineering at Politecnico di Torino, Italy, where he received his Bachelor's degree in 2017 and his Master's in 2020 with a thesis in collaboration with NASA Jet Propulsion Laboratory, California, USA, on modeling and simulation of the cardiovascular system in microgravity conditions. His research interests include electric powertrain design, platform-based, product-family design, and optimization.