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Concurrent Powertrain Design for a Family of Electric Vehicles

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Abstract:
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 three different vehicles: a city car, a compact car, and an SUV. Our results show that concurrently optimizing shared components increases the operational costs by 3.2% compared to individually tailoring them to each vehicle, a value that could be largely overshadowed by the benefits stemming from using the same components for the entire product family.

Keywords:
Electric vehicles, design methodologies, convex optimization, relaxations.

1. INTRODUCTION

The transition to sustainable energy and mobility is not progressing fast enough to meet objectives set by world leaders (UNEP and Partnership, 2021). 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 (IEA, 2020). 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.

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 (Verbruggen et al., 2019) and optimization strategies (Silvas et al., 2016). For instance, Hofman and Salazar (2020) jointly design

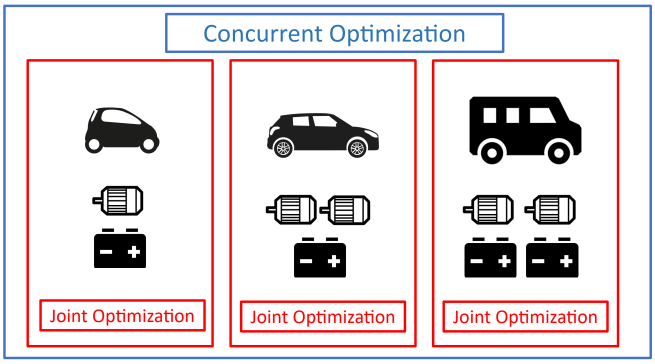

Fig. 1. Concurrent optimization design methodology.

powertrain and controls to minimize the energy consumption, while Borsboom et al. (2021) and Salazar et al. (2019) maximize performances. Anselma (2022) developed a Computer-Aided Engineering (CAE) tool to compare a predefined set of different hybrid topologies and sizes to find the most suitable for a fleet of cars. However, to the best of the authors' knowledge, whilst most methods do not account for multiple vehicles simultaneously, those who do are not focused on battery electric vehicles and do not have any global optimality guarantees.

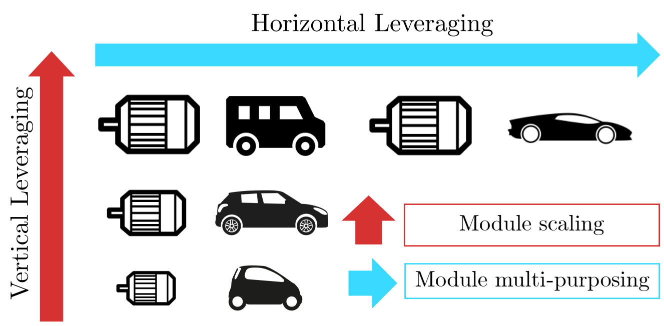

Fig. 2. Module-leveraging strategies in a family of vehicles.

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 (Jiao et al., 2007). They also foster the development and upgrade of differentiated products efficiently, increase flexibility and responsiveness in manufacturing processes (Robertson and Ulrich, 1998), and generate enormous savings in research, testing, interface design, and integration (Otto et al., 2016). 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 (Simpson et al., 2006), 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. Fellini et al. (2002a,b) 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 nominal power and battery capacity. 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 flexibility 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.

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 (Guzzella and Sciarretta, 2007) 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

$$S_{\mathrm{m}} \in [S_{\mathrm{m,min}}, S_{\mathrm{m,max}}] \subseteq \mathbb{R}_+ \quad (1)$$
$$S_{\mathrm{b}} \in [S_{\mathrm{b,min}}, S_{\mathrm{b,max}}] \subseteq \mathbb{R}_+. \quad (2)$$

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: $v(t)$

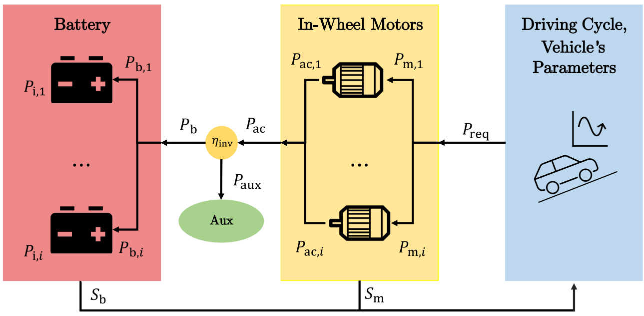

Fig. 3. Block diagram of a generic vehicle

and $a(t)$. For each vehicle, the required power P_{req} depends on aerodynamic drag, rolling friction, gravitational force, and inertial force.

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

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), driver, 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 $\overline{m}_{\mathrm{b}}$. Finally, the driver's mass $\overline{m}_{\mathrm{d}}$ is considered constant for every vehicle.

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

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

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

In case of negative power requirement, we introduce a regenerative braking fraction $r_{\mathrm{b},i}$ that the electric motors can exert without destabilizing the vehicle. 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:

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

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 Verbruggen et al. (2020):

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

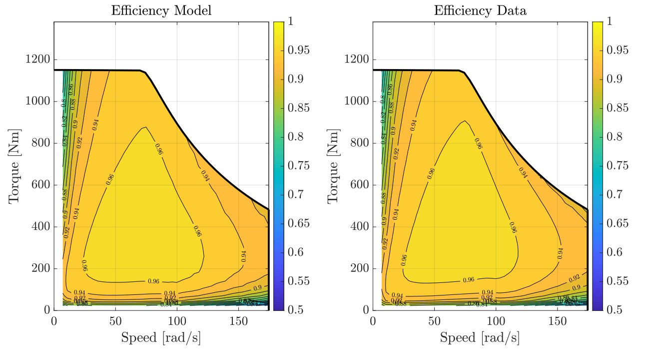

Fig. 4. Electric motor efficiency map from the model (left) compared with data (right).

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

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

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 input power of each motor $P_{\mathrm{ac},i}$ as

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

This approximation is particularly useful in this context since it allows to retain accuracy (NMRSE of 0.41%) and complexity, as shown in Fig. 4, without losing convexity. In fact, (7) can be relaxed to a convex second-order conic constraint, as will be shown in Section 3.1.

2.5 Battery

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

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

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:

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

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 Verbruggen et al. (2020), can be expressed as

$$P_{\mathrm{sc},i} = \min_k \{a_k \cdot E_{\mathrm{b},i} + b_k \cdot S_\mathrm{b}\}, \tag{9}$$

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

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

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

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

The energy consumption $E_{\mathrm{cons},i}$ 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 $E_{\mathrm{b},i}(T)$,

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

However, we consider the battery energy to stay within operational limits, leading to

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

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:

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

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 (König et al., 2021).

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 operational costs, and consequently the energy consumption, these constraints will always hold with equality. In fact, it is suboptimal to assume any higher value than the strictly necessary since it entails higher operational costs. 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

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

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

$$P_{\mathrm{b},i} \geq \frac{1}{N_{\mathrm{b},i}} \cdot \left(\frac{P_{\mathrm{ac},i} \cdot N_{\mathrm{m},i}}{\eta_\mathrm{inv}} + P_{\mathrm{aux},i}\right) \tag{17}$$

$$P_{\mathrm{b},i} \geq \frac{1}{N_{\mathrm{b},i}} \cdot (\eta_\mathrm{inv} \cdot P_{\mathrm{ac},i} \cdot N_{\mathrm{m},i} + P_{\mathrm{aux},i}), \tag{18}$$

whilst (7) and (10) can be expressed as second-order conic constraints (Ebbesen et al., 2018) as

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

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

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

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

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 speed at which the maximum torque and maximum power curves intersect, also called 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 J_{tot}, we select the sum of i different operational costs J_i, each one multiplied by the number of vehicles of that type $N_{\text{v},i}$ in the fleet

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

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*

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

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 (Grunditz and Thiringer, 2017). Finally, it is important to underline that, in our framework, the scaling factors are optimization variables, while the modules' multiplicities 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 realistic use case for this methodology: the concurrent design of a fleet composed of a city car, a compact car, and an SUV. The different parameters used in the optimization can be found in Table 1. In our analysis, we consider the Class 3 Worldwide harmonized Light-duty vehicles Test Procedure (WLTP) for the speed and acceleration trajectories, whilst reference motor and battery, minimum vehicle performance, and simulation parameters are provided in Tables 2, 3 and 4. We discretize Problem 1 using the Euler forward method with a sampling time of 1 s. Thereafter, we parse it with YALMIP (Löfberg, 2004) and solve it to global optimality with MOSEK (ApS, 2017), in approximately 2 s.

Our results show that sizing powertrain components concurrently causes an increment in the costs of operations of 3.2% for the family, compared to the individual vehicle-tailored optimization. In Table 5 it is evident how both the individual and concurrent approaches yield the same outcome for the SUV. This result is in line with our expectations: Since the SUV is the largest and heaviest vehicle in the family, it has the highest demands in terms of power required to complete the driving cycle (Fig. 5) and associated energy consumption. Nonetheless, thanks to the use of modularity and standardization, it is possible to satisfy the demands by adding more modules instead of increasing their size. Thus, in the concurrent design of the family, the city car and compact car both have one single battery module, whereas the SUV has two. The vehicle-specific increment in cost of operations is presented in detail in Fig. 6, where it is possible to notice different values for the city car and the compact car, depending on the approach. This difference can be ascribed to the fact that a module shared among the whole family may still be oversized for some vehicles to serve the entire fleet at best. However, for both vehicles, the increase in 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 6 and 7.

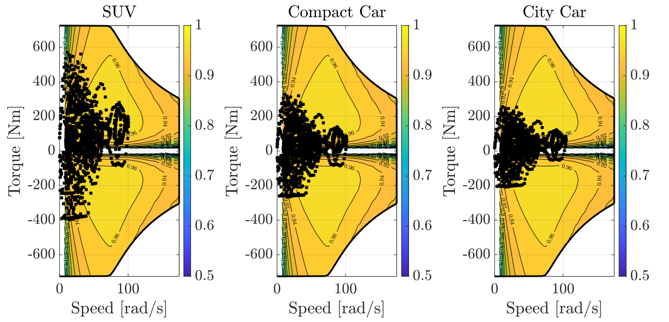

Fig. 5. Operating points of the electric motor module for the all the different vehicles in the family.

Even though the total cost of operations increases, it is expected that the benefits derived from using components shared by the entire product family will outperform the downsides (Jiao et al., 2007), prompting further research. In fact, car makers could exploit this methodology to set up the least amount of production lines possible while still being able to design a competitive family of vehicles, capable of serving various customer needs. Moreover, sharing the same type of modules allows further advantages in logistics, using the same parts to assemble a wide variety of products. Furthermore, the concurrent design of the family would bring many advantages also to users, reducing the cost and increasing the availability of spare parts. Specifically, this feature would be a huge advantage for an operator of a fleet of shared vehicles, since it allows to keep using the modules in good condition from a vehicle at the end of its service life.

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

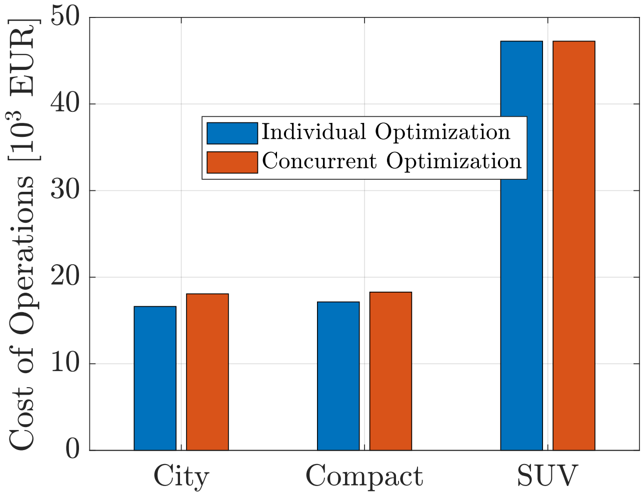

Fig. 6. Operational cost of the three vehicles sharing powertrain modules: a city car (left), a compact car (centre), and an SUV (right). The blue and the orange bars indicate the results attained with individual and concurrent optimization.

Table 1. Vehicles Parameters

Symbol	City Car	Compact Car	SUV	Unit
A_f	2.38	2.43	3.87	m^2
r_w	0.3498	0.3594	0.3630	m
c_d	0.29	0.23	0.31	–
c_r	0.01	0.008	0.02	–
η_inv	0.96	0.96	0.96	–
r_b	1	1	1	–
m_0	850	1250	2000	kg
m_d	85	85	85	kg
N_v	1	1	1	–

Table 2. Reference Motor and Battery Parameters

Symbol	Value	Unit
$\overline{m}_\mathrm{m}$	81.6	kg
$\overline{P}_\mathrm{m,max}$	89.38	kW
$\overline{m}_\mathrm{b}$	138.6	kg
$\overline{E}_\mathrm{b,max}$	23.48	kWh

Table 3. 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
θ_max	25	$\%$
D_range	300	km

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 three-vehicle family consisting of an urban car, a compact car, and a sport utility vehicle, our case-study revealed the potential of applying our novel methodology to a fleet 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 3.2%.

Table 4. Simulation Parameters

Symbol	Value	Unit
ξ_min	0.2	–
ξ_max	0.8	–
P_aux	500	W
D_year	20000	km
N_y	5	years
C_e	0.36	EUR/MJ

Table 5. Results from individual and concurrent optimization.

Symbol	Individual City	Individual Compact	Individual SUV	Conc. Opt.	Unit
S_m	0.25	0.34	0.63	0.63	–
m_m	20.55	27.79	51.45	51.45	kg
$P_\mathrm{m,max}$	22.50	30.42	56.33	56.33	kW
S_b	2.73	2.82	7.76	3.88	–
m_b	378	390	1076	538	kg
$E_\mathrm{b,max}$	64.12	66.13	182.31	91.15	kWh

Table 6. Family performance and configuratio as a result of individual design

Performance	City	Compact	SUV	Unit
Cost of Operations	16619	17142	47254	EUR
Vehicle Mass	1396	1837	3367	kg
Range	300	300	300	km
Acceleration Time	10.61	9.61	9.24	s
Top Speed	214	253	241	km/h
Energy Used	0.4616	0.4762	1.3126	MJ/km
N. of Motors	4	4	4	–
N. of Battery mod.	1	1	1	–

Table 7. Family performance and configuration as a result of concurrent design

Performance	City	Compact	SUV	Unit
Cost of Operations	18075	18277	47254	EUR
Vehicle Mass	1679	2079	3367	kg
Range	392	388	300	km
Acceleration Time	5.10	5.87	9.24	s
Top Speed	290	311	241	km/h
Energy Used	0.5021	0.5077	1.3126	MJ/km
N. of Motors	4	4	4	–
N. of Battery mod.	1	1	2	–

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, leveraging the computational speed of our approach to run a sequence of problems in a combinatorial manner.

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REFERENCES

Anselma, P.G. (2022). Electrified powertrain sizing for vehicle fleets of car makers considering total ownership costs and CO2 emission legislation scenarios. *Applied Energy*, 314, 118902.

ApS, M. (2017). MOSEK optimization software. Available at `https://mosek.com/`.

Borsboom, O., Fahdzyana, C.A., Hofman, T., and Salazar, M. (2021). A convex optimization framework for minimum lap time design and control of electric race cars. *IEEE Transactions on Vehicular Technology*, 70(9), 8478–8489.

Ebbesen, S., Salazar, M., Elbert, P., Bussi, C., and Onder, C.H. (2018). Time-optimal control strategies for a hybrid electric race car. *IEEE Transactions on Control Systems Technology*, 26(1), 233–247.

Fellini, R., Kokkolaras, M., Michelena, N., Papalambros, P., Saitou, K., and Perez-Duarte, A. (2002a). 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*.

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

Grunditz, E.A. and Thiringer, T. (2017). Modelling and scaling procedure of a vehicle electric drive system. Technical report, Chalmers University of Technology.

Guzzella, L. and Sciarretta, A. (2007). *Vehicle propulsion systems: Introduction to Modeling and Optimization*. Springer Berlin Heidelberg, second edition.

Hofman, T. and Salazar, M. (2020). Transmission ratio design for electric vehicles via analytical modeling and optimization. In *IEEE Vehicle Power and Propulsion Conference*.

IEA (2020). Global ev outlook 2020. Technical report, IEA, Paris.

Jiao, J., Simpson, T., and Siddique, Z. (2007). Product family design and platform-based product development: a state-of-the-art review. *Journal of Intelligent Manufacturing*, 18(1), 5–29.

König, A., Nicoletti, L., Schröder, D., Wolff, S., Waclaw, A., and Lienkamp, M. (2021). An overview of parameter and cost for battery electric vehicles. *World Electric Vehicle Journal*, 12(1), 21–50.

Löfberg, J. (2004). YALMIP : A toolbox for modeling and optimization in MATLAB. In *IEEE Int. Symp. on Computer Aided Control Systems Design*.

Otto, K., Hölttä-Otto, K., Simpson, T.W., Krause, D., Ripperda, S., and Moon, S.K. (2016). Global views on modular design research: Linking alternative methods to support modular product family structure design. *ASME Journal of Mechanical Design*, 138(7), 071101.

Robertson, D. and Ulrich, K. (1998). Planning for product platforms. *The Wharton Annual*, 39(4), 19–31.

Salazar, M., Duhr, P., Balerna, C., Arzilli, L., and Onder, C.H. (2019). Minimum lap time control of hybrid electric race cars in qualifying scenarios. *IEEE Transactions on Vehicular Technology*, 68(8), 7296–7308.

Silvas, E., Hofman, T., Murgovski, N., Etman, P., and Steinbuch, M. (2016). Review of optimization strategies for system-level design in hybrid electric vehicles. *IEEE Transactions on Vehicular Technology*, 66(1), 57–70.

Simpson, T., Siddique, Z., and J., J. (2006). *Product Platform and Product Family Design Methods and Applications*. Springer US, 1 edition.

UNEP and Partnership, D. (2021). Emissions gap report 2021: The heat is on – a world of climate promises. Technical report, United Nations Environment Programme and Technical University of Denmark.

Verbruggen, F.J.R., Rangarajan, V., and Hofman, T. (2019). Powertrain design optimization for a battery electric heavy-duty truck. In *American Control Conference*.

Verbruggen, F.J.R., Salazar, M., Pavone, M., and Hofman, T. (2020). Joint design and control of electric vehicle propulsion systems. In *European Control Conference*.