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Additional Information

Cost of ownership-efficient HEV powertrain sizing for multi-scenario driving cycles

Jose Manuel Luján, Carlos Guardiola, Benjamín Pla and Alberto Reig
 CMT - Motores Térmicos, Universidad Politécnica de Valencia, Valencia (Spain)
 e-mail: {jlujan, carguaga, benplamo, alreiber}@mot.upv.es

Abstract

During the last decade Hybrid Electric Vehicles have gained presence in the automotive market. At the street, in motorsports and in the society the hybrid vehicle is increasingly common. Many manufacturers had become involved in the business while some others have HEV projects in development. Thus, there is already a great variety of HEV in production – from small micro hybrids to range extenders.

Although there are some HEVs designed for urban driving or luxury segments, most of the market share is aimed to the same kind of use and driving, resulting in potentially sub- or oversized hybrid systems that could lead to an inefficient use of the vehicle's fuel saving capabilities in many situations.

The present work studies powertrain components (i.e. engine, motor and battery) size influence on fuel economy under different assumptions: urban, highway and mixed driving. The utilized framework permits the calculation of the theoretically optimum powertrain size assuming a particular target. Different drivers and traffic conditions are also evaluated. Finally, a long-term cost evaluation is carried out to estimate the optimal size of the HEV powertrain as a function of vehicle's type of use along its life-cycle.

Index Terms

Hybrid Electric Vehicle; Energy Management; Optimal Control; Dynamic Programming; Powertrain Size

I. INTRODUCTION

NOWADAYS Hybrid Electric Vehicles (HEV) are a trending technology that joins the versatility of traditional powertrains and the economy of electric vehicles. The growth of this technology within the automotive market is quite significant for an industry that traditionally has been reticent to big changes [1]. During the last decade, the market share for HEV has increased from 2,200 registrations in 2001 to 72,500 in 2009 and 131,700 in 2012 [2] and the forecast is to reach about 943,300 registrations for 2020 [3] in Europe.

The huge diversity of HEV concepts in the market shows the increasing interest of manufacturers for this kind of vehicles. Micro hybrids, mild hybrids, full hybrids, plug-in hybrids or even range extender vehicles are already in production (the interested reader may find a detailed dissertation on these type of vehicles on [4]–[6]). Also, manufacturers are slowly increasing the size of their HEV's battery pack since customers are usually cautious about the reduced electric range in what [7] calls driver's *range-anxiety* – however this results in a heavier and more expensive vehicle. This has become a main topic in literature resulting in many studies related to the proper management of batteries temperature [8] and consideration of battery aging [8], [9] in order to extend its lifecycle for a given technology. Nevertheless, battery chemistry is rapidly evolving with a vast

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variety of available components, some of them being quite widespread in the automotive industry such as Ni-MH and Li-Ion [4].

Apparently there is no consensus on the adequate size of components (engine, motor and battery) for an optimized vehicle operation. For example, it is possible to find HEVs in the same segment and aimed to similar uses with battery packs ranging from approximately 0.5 kWh to more than 15 kWh. Of course, on one hand an oversized hybrid system gives an extra performance and versatility that probably would not be profited while increasing vehicle's weight and price in such a way that the investment will never be overcome; on the other hand, an extremely mild electrification of the vehicle would reduce the fuel saving capacity to insignificant values. This issue has motivated the proposal of more sophisticated approaches such as supercapacitors [10], [11], fuel cell [5], [12], [13] and battery-supercapacitors [14]–[17] powered hybrid powertrains.

Several studies have been focused on this topic, where optimal powertrain sizing methodologies are developed based on different criterias. Usually a cost index is defined, including fuel consumption, vehicle cost or pollutant emissions, and an optimization method is employed to reach a global minimum to the problem. Many works rely on genetic algorithms [18], [19] or particle swarm optimization [20], [21] to surf across a space of component size candidates. Other studies make use of convex optimization techniques [22], mainly Pontryagin minimum principle, mixing the control strategy optimization and battery sizing into one single problem [23] or to guarantee the optimal operation of the powertrain at any component size combination [24]. Vehicle performance is commonly introduced in the optimization problem in the form of an additional constraint that bounds the space of candidates as approached in [20].

Previous works have been addressed to detailed cost analysis of vehicle electrification and hybridization, such as [25], [26], where models and valuable tools for powertrain cost and weight estimation are deeply studied.

In [27] authors proposed a multi target hybrid electric powertrain sizing framework based on dynamic programming (DP). The method offers the optimal sizing solution for powertrain components based on vehicle marketing concerns –such as dynamic performance– and homologation driving cycles by providing a scalable vehicle model.

Following the studies of [27], the present work also involves a powertrain optimal sizing methodology but from a user economy point of view. addressing the total cost of ownership. Main contributions are:

- Estimate the best, theoretically optimum, affordable fuel economy for a type of driver on a HEV, based on DP methodology.
- Propose a powerful methodology to optimally fit a HEV powertrain to a specific type of vehicle use –i.e. a market niche– maximizing economy based on expected driving conditions instead of an arbitrary weighted specifications.
- Calculate the proper powertrain component size in a parallel HEV for an expected type of use and mileage, minimizing the lifetime cost including purchase price.
- Analyze the optimal powertrain size sensitivity to differences in driving style and cycle, evaluating different drivers and routes.
- Find out the importance of a well sized HEV on fuel efficiency and long term economy.

For this purpose this paper is organized as follows: in section II the approached HEV model is stated followed by problem description, powertrain scaling and price/weight estimation methodology. Section III goes through the developed methodology and summarizes the proposed analysis. Then, in section IV optimization results are presented and several studies are carried

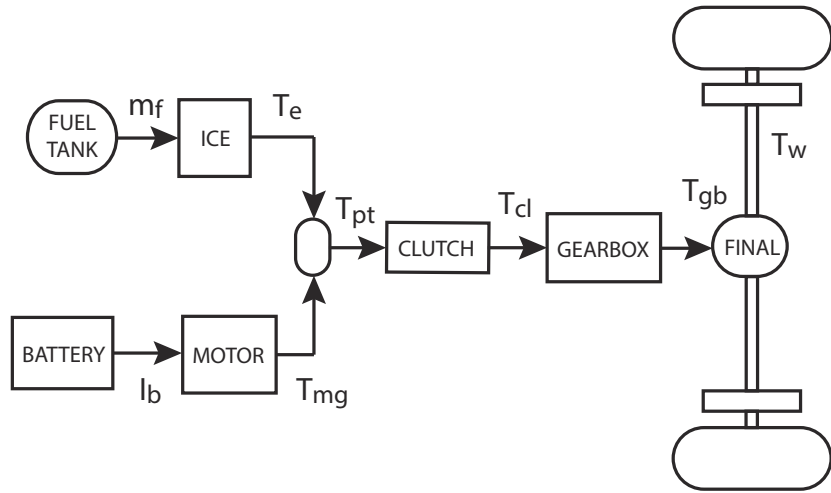


Fig. 1: Implemented parallel hybrid electric vehicle layout with main energy flow labels

out such as a payback period analysis for an average driver as well as Pareto and sensitivity analysis of optimal HEV size. Finally, in section V some conclusions are stated and interesting future works proposed.

II. PROBLEM FORMULATION

The aim of this methodology is to calculate the adequate powertrain component size of a parallel HEV for a specific type of use. This involves the evaluation of an optimization problem that includes, not only the traditional energy management problem [28], [29], but also the selection of the appropriate engine, motor and battery size. The optimization target is both fuel economy [30], [31] and user initial investment in such a way that the total cost undertaken by customer is minimized for the vehicle lifetime cycle. Note that the parallel layout is used through the paper as an example, but the formulation is equivalent for any other topological architecture and its implementation may be almost straightforward.

The size fitting problem is stated as a global optimization problem. The simplest approach consists of a given set of constraints and disturbances (namely speed profile, road grade and gear number), and a set of inputs (engine, motor and battery sizes, and control strategy as well) that is selected such that the fuel consumption along a cycle is minimized, as formerly stated in [27]. This step is a prerequisite to lately select the powertrain size that minimizes not only fuel consumption but the whole lifetime ownership cost.

This task requires a HEV simulation model that estimates the fuel consumption as well as other relevant outputs (e.g. battery state of charge dynamics). This model and the employed optimization method will be presented in the following points. The method splits the optimum seeking procedure into two steps, where in first place the control strategy is optimized with dynamic programming generating a space of optimum candidates, and then the size of the powertrain components is optimized attending to the total cost of ownership. Both steps are detailed in II-B.

A. HEV layout

The present work has been performed on a parallel hybrid vehicle, whose scheme is depicted in figure 1. However, the same study may be done with any other hybrid architecture with minor changes. The vehicle is modeled in a backwards fashion

(the interested reader might want to check [32] for detailed information on backwards modelling of HEV powertrains) with one degree of freedom, namely the instantaneous current drawn from the battery, $u(t)$. The model is completely defined with one state $x(t)$: the battery state of charge (SoC). Therefore, vehicle speed, acceleration, road grade and gear number are just inputs to the problem (disturbances) since they are known *a priori*.

Due to the quasi-static nature of the backwards modelling [32], both motor and engine are based on their static equivalent operation maps. On the one hand, the electric motor torque, T_{mg} , as a function of the current $u(t)$, can be expressed as:

$$T_{mg} = T_{mg}(\omega_{mg}, P_{mg}(u)) \quad (1)$$

where T_{mg} is mapped, ω_{mg} is the rotational speed of the motor and $P_{mg}(u)$ is the electric power utilized, expressed by:

$$P_{mg}(u) = u \cdot V_{dc} \cdot \eta_{conv} \quad (2)$$

V_{dc} is the voltage at the battery terminals and η_{conv} the DC/DC converter efficiency. η_{conv} is considered fixed at 85% and V_{dc} equal to open circuit voltage (200 V).

On the other hand, the engine torque, T_{ice} , is mapped as:

$$T_{ice} = T_{ice}(\omega_{ice}, F) \quad (3)$$

being ω_{ice} the engine rotational speed and F the injected fuel rate. ω_{ice} is a result of the rotational speed of the gearbox output shaft, ω_{gb} , and the selected gear. This can be expressed as:

$$\omega_{ice} = \omega_{gb} \cdot R_{gb}(n_{gb}) \quad (4)$$

where R_{gb} is the gearbox transmission ratio of gear number n_{gb} . The gearbox torque transmission efficiency is considered fixed at 95% (η_{gb}).

The torque split is performed on the gearbox upstream and must verify that:

$$T_{pt} = T_{ice}(u) + T_{mg}(F) \quad (5)$$

T_{pt} is the combined torque output of the powertrain which is constrained to:

$$T_w = T_{pt} \cdot R_{gb} \cdot \eta_{gb} \cdot R_{fd} \cdot \eta_{fd} \quad (6)$$

where R_{fd} is the final drive transmission ratio and η_{fd} its efficiency (fixed at 98%). T_w is the torque at the wheels, which is calculated based on the input vehicle speed and acceleration. The considered losses in the vehicle are inertia, road friction, aerodynamic drag and road grade effect:

$$T_w = T_{inertia} + T_{road} + T_{drag} + T_{grade} = (m\dot{v} + fmg \cos(\alpha) + 0.5\rho C_d S v^2 + mg \sin(\alpha)) \cdot r_w \quad (7)$$

where m is the vehicle mass, f the road friction coefficient, g the gravitational acceleration, α the road grade, ρ the air density, C_d the vehicle drag coefficient, S the reference area, v the vehicle speed and r_w the wheel radius.

B. Problem description

Given the above powertrain scheme, the total fuel consumption F_{tot} along a cycle may be expressed as:

$$F_{tot} = \int_0^T F(v, \dot{v}, \alpha, n_{gb}, u, t) dt = \int_0^T F(u, t) dt \quad (8)$$

where v , \dot{v} , α and n_{gb} are known in advance and may be considered disturbances of the problem.

If engine, motor and battery main design parameters (displacement V_d , power \hat{P}_{mg} and capacity Q respectively) are considered free variables, the total fuel consumption increases its d.o.f. in three units:

$$F_{tot} = \int_0^T F(u, V_d, \hat{P}_{mg}, Q, t) dt \quad (9)$$

Therefore, the optimal HEV powertrain size is such that minimizes the total fuel consumption along a driving cycle:

$$\min_{V_d, \hat{P}_{mg}, Q} \left\{ \min_u \left\{ \int_0^T F(u, V_d, \hat{P}_{mg}, Q, t) dt \right\} \right\} \quad (10)$$

Note that the global minimization problem has been split into two steps: control strategy optimization and size optimization, which is performed over the domain of $\min_u\{\cdot\}$.

Given V_d , \hat{P}_{mg} and Q , the HEV control strategy is such that achieves the minimum possible fuel consumption along the driving cycle. Thus, the energy management problem (EMP) is solved by means of a global optimization method. The EMP may be stated as the minimization of the fuel consumption during the cycle, given by the performance index J :

$$\min_u \left\{ \int_0^T J(u(t), x(t), t) dt \right\} \quad (11)$$

where the J function is an expression of any complexity –in this work defined by the model in section II-A– that calculates fuel consumption along a cycle of length T . Note that J must be fully defined, i.e. the problem is solved individually for a particular powertrain size.

Equation 11 is constrained in such a way that model state $x(t)$ –namely the battery SoC– is forced to reach an arbitrary value at the end of the problem. For a parallel HEV the battery is typically forced to reach the same SoC at the end than at the beginning of the cycle, as opposed to plug-in HEV [33]:

$$\frac{\int_0^T u(t) dt}{Q} = -\Delta SoC = 0 \quad (12)$$

so charge is sustained. However, this constraint is very restrictive and could lead to a sub-optimal solution when applied to a problem above T (e.g. vehicle lifetime cycle); this will be discussed later in this paper.

State, SoC, and control variable, u , are also constrained because of physical limits of the powertrain as well as intermediate variables such as torques or rotational speeds. Finally, speed, acceleration and road grade are specified as disturbances to the optimal problem.

This problem can be solved with the reader's choice optimal method. However, due to the non linearity of J , solvers such as LP or QP are not suitable. Authors decided solving the problem with dynamic programming –like [34], [35] and as firstly suggested in literature by [36] for the component sizing task– using the generic DP Matlab toolbox provided in [37]. The main reason of the selection of this method is that it is able to numerically find the global optimum of a problem of any complexity (at the expense of computational time and memory) since it is based on the HJB equation which is a sufficient condition for global optimality. However Pontryagin minimum principle could also be perfectly used when sufficient conditions are provided.

C. Powertrain scaling

The three main powertrain elements suitable to be scaled in terms of fuel economy are: engine, electric motor and battery. These components are modeled by means of mathematical expressions as stated in section II-A. Of course, for the scope of this work, these models must be scalable, i.e. capable of representing similar machines of different sizes, both in specifications and weights as stated in [27].

The engine is based on its equivalent quasi-static maps and it is scaled attending to the displacement. On one hand performance specifications are defined by maximum and minimum torque curves, which are given for a specific displacement. For a particular bore/stroke ratio and engine technology, MEP could be considered an invariant regardless of the displacement [38]. Then, the maximum and minimum torque may be calculated for any equivalent engine as:

$$T_{ice} = \frac{MEP \cdot V_d}{2\pi \cdot n_c} \quad (13)$$

where V_d is the displacement and $n_c = 2$ for a four stroke engine. On the other hand, fuel mass flow F is estimated from engine efficiency:

$$F = \frac{1}{H_c} \cdot \frac{T_{ice} \cdot \omega_{ice}}{\eta_{ice}} \quad (14)$$

where η_{ice} is mapped for the reference engine and heat of combustion H_c is fixed for a particular fuel. Assuming that heat losses increases with cylinder exchange surface, the efficiency map may be estimated as follows:

$$\eta_{ice} = \frac{1}{1 + T_{loss}/T_{ice}} \quad (15)$$

where resized engine losses are estimated as a fraction of the reference engine losses, $T_{loss,ref}$ and exchange surface, $A_{exch,ref}$:

$$T_{loss} = T_{loss,ref} \cdot \frac{A_{exch}}{A_{exch,ref}} \quad (16)$$

To estimate the weight of the engine a statistical analysis has been done. Several production vehicles were selected and their homologation weight versus displacement was represented. Those points were approached to a linear equation where the slope, k_{ice} , is the contribution of the engine to the weight, under the assumption that different motorizations in the same vehicle does not include any extra equipment. Therefore, the engine weight is calculated as:

$$W_{ice} = k_{ice} \cdot V_d \quad (17)$$

The electric motor is also based on a quasi-static map, that defines motor efficiency η_{mg} for every pair of motor speed ω_{mg} and electrical power P_{mg} . The motor is scaled according to its maximum power consumption. Assuming the same electrical characteristics, with no dependency on the motor size, the torque may be calculated as:

$$T_{mg} = \frac{P_{mg} \cdot \eta_{mg}}{\omega_{mg}} \quad (18)$$

where P_{mg} is limited by maximum motor specifications and, consequently, maximum torque. The motor is considered as a fully reversible machine so the operation map can be scaled to any of the four speed/torque quadrants following the same scheme.

The weight of the motor is calculated based on the approach explained in [25]. Thus, the weight of the motor is divided into weight of electronics $W_{mg,1}$ –which is fixed regardless of the size– and the weight of the electrical machine $W_{mg,2}$:

$$W_{mg,2} = k_{mg} \cdot \hat{P}_{mg} \quad (19)$$

where \hat{P}_{mg} is the maximum electrical motor power. Then, the weight of the motor is estimated as:

$$W_{mg} = W_{mg,1} + W_{mg,2} \quad (20)$$

The battery is represented as an ideal voltage source and a resistance in series. The resistance is variable with SoC but constant with battery capacity. Therefore, scaling the battery capacity does not impact to any other battery specification.

The weight of the battery is also estimated following the approach presented in [25]. Then, the battery weight may be divided into the contribution of four terms: the battery chemicals ($W_{b,1}$), the tray ($W_{b,2}$), the thermal management system ($W_{b,3}$) and buses, harnesses and terminals ($W_{b,4}$). The first term depends only on the type of battery since the amount of chemicals of specific energy e needed to store an amount of energy E weights:

$$W_{b,1} = \frac{E}{e} \quad (21)$$

The second and third terms are expressed as a function of the battery capacity since the biggest the battery is, the heaviest the

thermal system and battery tray are:

$$W_{b,2} = k_{b,2} \cdot Q_b \quad (22)$$

$$W_{b,3} = k_{b,3} \cdot Q_b \quad (23)$$

Finally, the last term is proportional to the maximum battery power output \hat{P}_b as the size of buses, harnesses and terminals depend on the maximum current that may flow and not the capacity of the battery:

$$W_{b,4} = k_{b,4} \cdot \hat{P}_b \quad (24)$$

Therefore, the total weight of the battery is:

$$W_b = W_{b,1} + W_{b,2} + W_{b,3} + W_{b,4} \quad (25)$$

D. Vehicle cost

In an optimal HEV powertrain sizing, two terms come into action: the efficiency of the elements and the price of the powertrain. Of course, depending on the use and the mileage one term might become more important than the other. Therefore, the price of the powertrain should be estimated in a scalable way as it was done for the weight and models in section II-C.

The cost of the engine is estimated directly from the displacement:

$$C_{ice} = c_{ice} \cdot V_d \quad (26)$$

where the coefficient c_{ice} depends only on the type of fuel; the breathing method does not really matter since only a 0.08% of diesel engines at the european market are naturally aspirated and turbocharged gasoline engines are sold at approximately naturally aspirated prices. This coefficient was estimated from engine prices for consumer (price for a full engine without accessories at original spare parts service) for both diesel and gasoline engines. The agreement between equation 26 and real data may be advised on figure 2.

The motor and its electronics cost is calculated as stated in [25]. It proposes an empirical equation that estimates the manufacturer cost C_{mg}^* as:

$$C_{mg}^* = c_{mg,1} + c_{mg,2} \cdot \ln(\hat{P}_{mg}) + c_{mg,3} \hat{P}_{mg} \quad (27)$$

However, since engine estimated cost is at the customer level, the above motor cost must be translated. The main differences between manufacturer and customer cost are taxes and OEM profit. Assuming that both are a fixed percentage, the final customer cost may be expressed as:

$$C_{mg} = c_{mg,4} \cdot C_{mg}^* \quad (28)$$

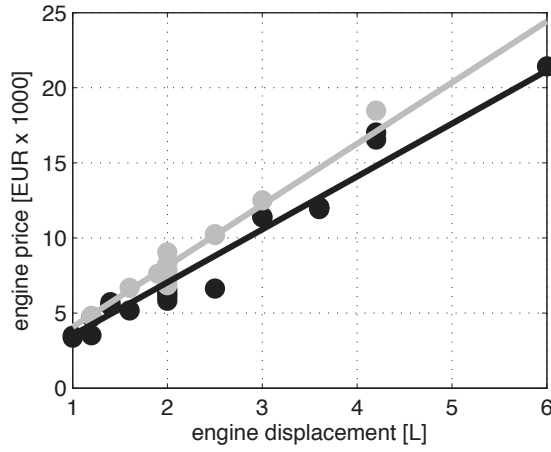


Fig. 2: Polynomial fitting of consumer engine price as a function of displacement; black color corresponds to gasoline and grey to diesel

The coefficient $c_{mg,4}$ might be estimated with the trade-off between original spare parts service prices and their corresponding manufacturing cost estimations.

The cost of the battery is also estimated following the method explained in [25]. Simplifying the algorithm, the battery cost results:

$$C_b^* = (c_{b,1} + c_{b,2}) \cdot W_{b,1} \quad (29)$$

where $c_{b,1}$ is a reference battery manufacturing cost and $c_{b,2}$ the accessories cost, both expressed per kilogram. $W_{b,1}$ is the chemicals weight, calculated in equation 21. Again, this cost is expressed as a manufacturing cost, so with the same assumption than in the motor, the customer cost may be estimated as:

$$C_b = c_{b,3} \cdot C_b^* \quad (30)$$

where coefficient $c_{b,3}$ is also estimated with original spare parts service price versus manufacturing cost estimation trade-off.

Finally, the vehicle cost C_{veh} –without powertrain– is fixed for the whole work. A reference value was adopted corresponding to a 4-doors and 5-seats sedan vehicle. Then, the total cost of the HEV is calculated as:

$$C_{hev} = C_{veh} + C_{ice} + C_{mg} + C_b \quad (31)$$

III. METHODOLOGY

The performance of a particular set of machines (namely engine, motor and battery) is evaluated simulating the scalable HEV presented in section II-A with a diesel engine map along a predefined driving cycle. First, the machines are scaled to the desired sizes and cost of the vehicle is calculated. Following, the optimal control strategy is computed, solving the optimization problem stated at section II-B. Finally, the fuel efficiency of the HEV is computed simulating the optimal control strategy along the driving cycle. This task is repeated for every powertrain component size combination building a set of candidates.

	Minimum	Maximum	Intermediate points
Engine (cc)	250	2500	19
Motor (kW)	0	100	21
Battery (Ah)	0	70	15

TABLE I: HEV powertrain size range of variation

In order to evaluate different fields of application, the above calculations were done for two types of driving cycles: city and highway. However, this does not constrain calculations to two single cycles; as a matter of fact, the methodology consists of building city/highway mixed cycles from several real cycle samples with different city driving contribution, from 0 to 100%, comprising a wide variety of use conditions.

A. *Minimum seeking*

The optimal HEV size for a particular driving cycle and its corresponding fuel efficiency are computed. The optimization is performed attending only to driving cycle performance regardless of the vehicle price. For this purpose, the engine, motor and battery sizes are combined together, bounded to the values indicated at table I. This implies the computation of 5985 different cases for a driving cycle. At each case the optimal control trajectory is computed with dynamic programming and its fuel economy is assigned to the corresponding candidate.

Once all cases have been optimized and simulated, the minimum fuel consumption among all candidates is selected and its corresponding HEV size is adopted as the best constructive solution that the vehicle may adopt to maximize fuel economy in that particular driving cycle.

B. *Multi-scenario*

The HEV size optimization is computed under diverse situations and for different applications: various drivers and routes. The influence of driver in the optimal size is studied with a set of driving cycles (both city and highway) belonging to different non-professional drivers. For every cycle the same control strategy optimization and minimum seeking algorithm is used.

The type of route may also affect to the optimal HEV size. Therefore, a set of city and highway driving cycles have been analyzed. Those cycles not only represent a different route or type of application but also traffic conditions and time/day effects, which could lead to a different vehicle selection to minimize cost.

An HEV must be aimed to a diversity of drivers with different needs, so no benchmark driving cycle is known in advance. Since the HEV machines selection relies mostly on the use of the vehicle, an evaluation with an incorrect cycle could lead to a non-efficient HEV size. Therefore, a sensibility analysis of size selection is performed varying the city driving contribution to the HEV utilization from an all-highway use to pure city driving. Thus, 11 driving cycles have been built concatenating city and highway cycles in random order and weighting the amount of city mileage from 0 to 100%. To prevent effects of problem terminal constraint (equation 12) every combined driving cycle is made of 50 individual driving cycles, so the new cycle represents about one month of daily utilization (and consequently the terminal constraint impacts about 50 times less in optimization solution).

	Minimum	Maximum	Intermediate points
Engine (cc)	200	2000	6
Motor (kW)	0	90	4
Battery (Ah)	0	100	5

TABLE II: HEV powertrain size range of variation for use sensibility analysis

For this last case, problem discretization is downgraded from values at table I to values at table II for computational reasons, narrowing the range closer to the former optimal solution. However, around optimum the previous discretization was maintained.

C. Long term optimization

For homologation purposes the only thing that matters in a vehicle is to achieve the best fuel economy (with compliment with emissions legislation). However, a vehicle should be sold at a reasonable price. From the customer point of view, the key point is the long-term cost: the driver does an investment at the time of the purchase and, if he did the appropriate selection, during vehicle's life he will save money in fuel compared to any other alternative. The best solution for him is a good trade-off between a reasonable investment and a cheap operation. Of course, none of those options means that the best solution implies the cheapest car neither the most efficient one.

Therefore, based on the results of the study presented in the previous section, a long-term cost optimization is done. The total cost per kilometer C_{km} is estimated for every possible HEV size combination at different mileages as:

$$C_{km} = \bar{F} \cdot c_f + \frac{C_{hev}}{mil \cdot n} \quad (32)$$

where \bar{F} is the average fuel consumption in liters per kilometer, c_f is the cost of fuel per liter, mil is the mileage per year, C_{hev} is the total HEV cost and n is the life cycle of the vehicle, in this case 10 years. Then, selecting the cheapest operation cost per kilometer C_{km} for each mileage, the trade-off between mileage and optimal HEV size may be computed.

IV. RESULTS

The scalable HEV model indicated in section II-A has been simulated along several driving cycles. There were two non-professional drivers (A and B) available to record real driving cycles, recording both city and highway driving cycles from each one. The HEV operation was simulated iteratively with different engine, motor and battery sizes, ranging within the grid specified at table I. An optimal control strategy was computed with DP prior to each simulation.

The simulation of the multiple HEV powertrain size combinations resulted in a 3-dimensional space of optimal achievable fuel economy values. In particular, some slices of this space of solutions (driver A, city driving) may be advised in figure 3, split at different battery sizes. Results show that the most efficient operation points tend to fall in the lowest engine displacement zone; naturally, increasing the engine size spoils the fuel economy at any situation, since engine works at lower loads –i.e. lower efficiency–. In contrast, battery and electric motor size not always impact significantly on fuel economy.

The maximum amount of energy that can transit on one direction is limited by the battery capacity. Incorporating a bigger electric motor does not mean that the extra power can be used and, therefore, exists a boundary profitable motor power

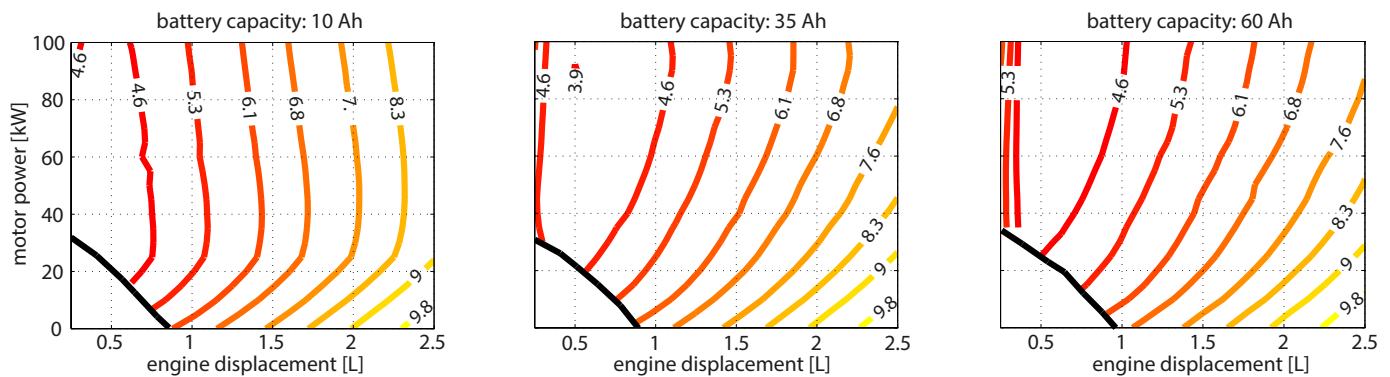


Fig. 3: Fuel economy solution space at different battery sizes, simulated with driver A and city operation.

–depending on driving cycle–; any motor above that power would not offer any advantage and, usually, will decrease fuel economy due to its greater mass and oversized specifications. In the left hand side plot of figure 3 it may be appreciated that, for a given engine size, above a motor power of 25 kW the fuel economy does not change too much and, in fact, it slightly decreases. Of course, increasing the battery size permits profiting a more powerful motor so the motor power for minimum fuel consumption moves to higher values. In the middle and right plots the turning point moved upwards out of the figure due to this effect. In addition, since the battery is like an energy buffer that compensates the differences along the driving cycle, depending on the aggressiveness and (mostly) on the length, the maximum amount of energy that can be stored (regardless of the motor power) is limited. Therefore, above that limit no extra energy can be buffered and a battery size increase will not improve fuel efficiency. Similarities in the middle and right plots of figure 3 show that the boundary battery capacity has been reached –and eventually exceeded–.

Based on the previous discussion it is clear that battery size is bounded by *bufferable* driving cycle energy in the same way that the motor size is bounded by battery size. Therefore, powertrain size is globally bounded so overcoming those values do not contribute to improve fuel economy anymore. Based on figure 3 those limits can be intuited: exceeding 80 kW and 35 Ah makes no sense and, in fact, the optimum solution is 0.4 liters / 65 kW / 25 Ah (engine/motor/battery). Small engines work at higher loads, that means better efficiency, but they also have increased losses compared to their power output. Hence there is an optimum size that balances both effects, which can be intuited from figure 3 to be about 0.3 ~ 0.5 liters. However, since all the vehicle energy comes ultimately from fuel, tiny engines could be unable to follow the driving cycle. This issue may be also appreciated at figure 3 where the bottom left zone is empty due to the inability of the HEV to follow the cycle.

The 3-dimensional space of solutions could be also evaluated with a Pareto frontier analysis. The minimum fuel consumption is extracted from the space of solutions so any duplet of sizes gives the optimal third size and its fuel economy as depicted in figure 4. In this case the optimal battery size is expressed as a function of engine displacement and electric motor power. Some of the conclusions drawn in the previous discussion may be also applied here: the minimum fuel consumption is quite similar to that from any plot in figure 3 that overcomes the 35 Ah boundary capacity since bigger batteries do not facilitate the energy recovery anymore. Also as the battery limits the maximum energy that can be buffered, the motor power gets limited, resulting in a strong relation between motor power and optimal battery size that may be appreciated in the right plot in figure 4 at almost all the studied area; however, this relation is no longer valid on the upper left zone –very small engine and big

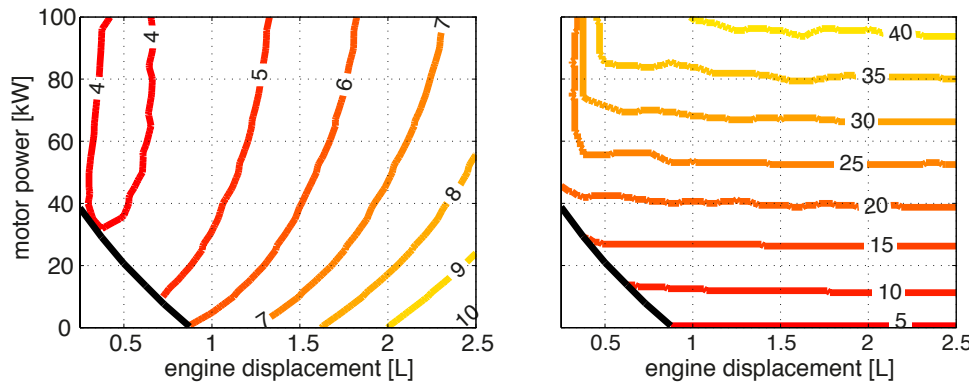


Fig. 4: Pareto frontier analysis of powertrain sizes listed by engine displacement and motor power, in the case of driver A and city driving. Left plot contours show fuel consumption in liters per 100 kilometers; right plot contours show battery capacity in Ah.

motor-. In that zone the engine is as small that cannot follow the driving cycle by itself (on the bottom –with no motor neither battery– the solution does not exist), so even being the vehicle capable of it with the help of the electric motor, this engine inability limits the amount of energy that can be buffered along the cycle. Anyway, with the sufficient engine performance, there is a quasi-univocal relation between motor and battery sizes regardless of the engine.

Some size sensitivity conclusions may also be extracted from the Pareto analysis. It is obvious that engine displacement strongly affects fuel economy, however motor power (and consequently battery capacity) slightly impacts on the resulting fuel consumption. Of course, when moving close to a non-hybrid powertrain (small motor and battery) the influence grows. An explicit analysis evaluating the gradient around the optimal solution also results in the same conclusions, where the gradients in liters of fuel per 100 kilometers are 3.02 (per liter of displacement), 0.003 (per kW) and 0.007 (per Ah) for the engine, motor and battery sizes respectively.

Assuming that a vehicle purchase is an investment for the buyer, the costs may be splitted into two components: fixed costs (vehicle price) and variable costs (fuel consumption). Of course other costs may be included from an economical point of view such as service, annual taxes, etc., but since those do not explicitly depend on the powertrain size they are neglected for a long term study. Taking into account fixed and variable costs as well as the use of the vehicle (mileage), the cost of the investment could be evaluated for a returning period. Thus, the cost per kilometer was calculated through the space of solutions for different mileages and a life time of 10 years. The minimum (optimal) cost as a function of the mileage is depicted in the upper left plot of figure 5. Also, its corresponding powertrain size (engine, motor and battery) is shown in the right and bottom plots.

Of course, one important factor on a long term cost minimization could be the battery lifespan and efficiency along time. Battery life-cycle could deform the theoretical optimum to, for example, a bigger battery to minimize the number of charge/discharge cycles for a given mileage. The interested reader may find an extended discussion of components sizing and battery life-cycle at [22].

Long term cost and sizes asymptotically tends to the optimum from the space of fuel consumption solutions: for an infinity long distance, the fixed cost loses its weight so only variable costs matters. On the other side, for zero operation, the best option is the cheapest vehicle which, of course, mounts the smallest powertrain –including a null motor and battery so basically

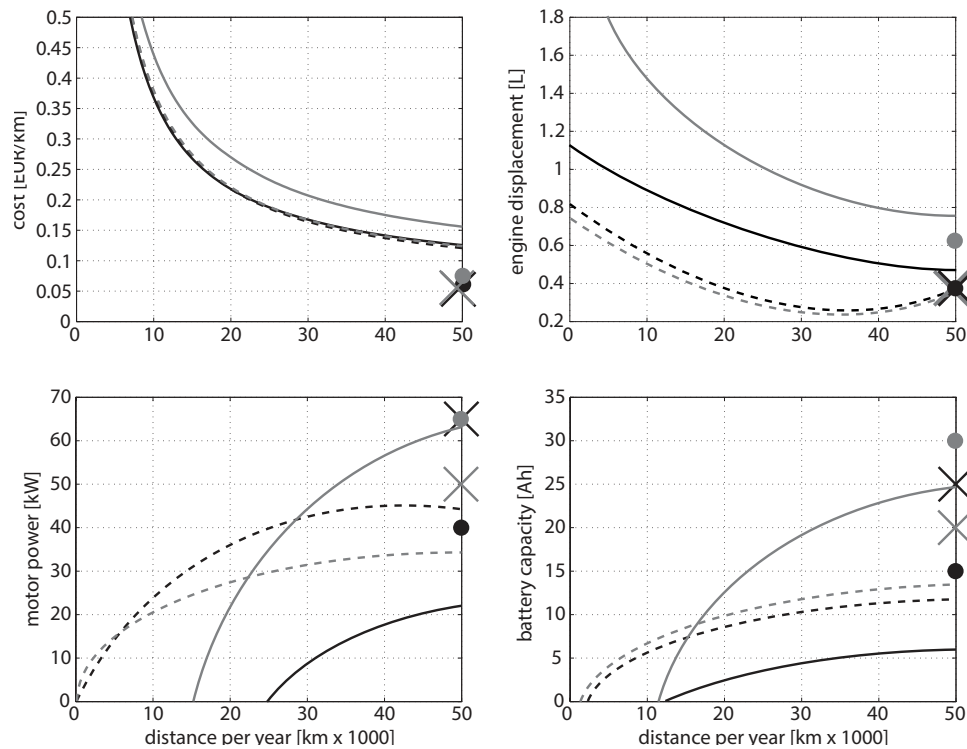


Fig. 5: Optimal operation cost (top left), engine displacement (top right), motor power (bottom left) and battery capacity (bottom right) as a function of mileage per year in terms of minimum operation cost per kilometer. Dashed lines and crosses are city driving while solid lines and points are highway operation; black color corresponds to A-driver's cycle while gray is B-driver's cycle. Points and crosses on the right of each plot are the infinity mileage optimums.

it is not a hybrid-. The transition from one powertrain to another depends on the relation between fixed and variable costs: if the optimum HEV is not much more expensive than the cheapest one, the best option rapidly evolves to that optimum with a little increase in mileage, which is the case of some cycles in figure 5.

To evaluate the effect of the driver style two non-professional drivers were asked to record their daily cycles with a natural driving style. The result of the size optimization of both drivers cycles resulted in the long term trade-off shown in figure 5 –black lines correspond to A-driver's cycle and gray to B-driver's cycle-. It may be appreciated that the minimum operation cost as well as the optimal size is approximately the same for both drivers.

Reader should take into account that a long term trade-off is a cost evaluation and it depends on the purchase price of the vehicle. The most expensive components –increasing vehicle cost the most- vary less with driving cycle since a bigger unit is difficult to redeem with its corresponding improvement in fuel economy. This means that the gradient between the long-term and the fuel efficient optimums defines the sensitivity of the size with respect to driver style. In other words, battery and motor sizes are strongly driver style dependent as those machines are slightly cheaper than engine, offering a wider variety of long term solutions. For example, as driver B city driving style is more aggressive than A (average power requirement of 5 and 3 kW respectively), his optimal powertrain size is slightly bigger than that from driver A.

A similar study may be done for different types of driving cycle. Since driver A and B recorded their daily routes, both city and highway driving cycles were available and another long term trade-off was computed and depicted in figure 5 –dashed lines correspond to city driving and solid lines to highway-. While for different drivers no significant differences were appreciated

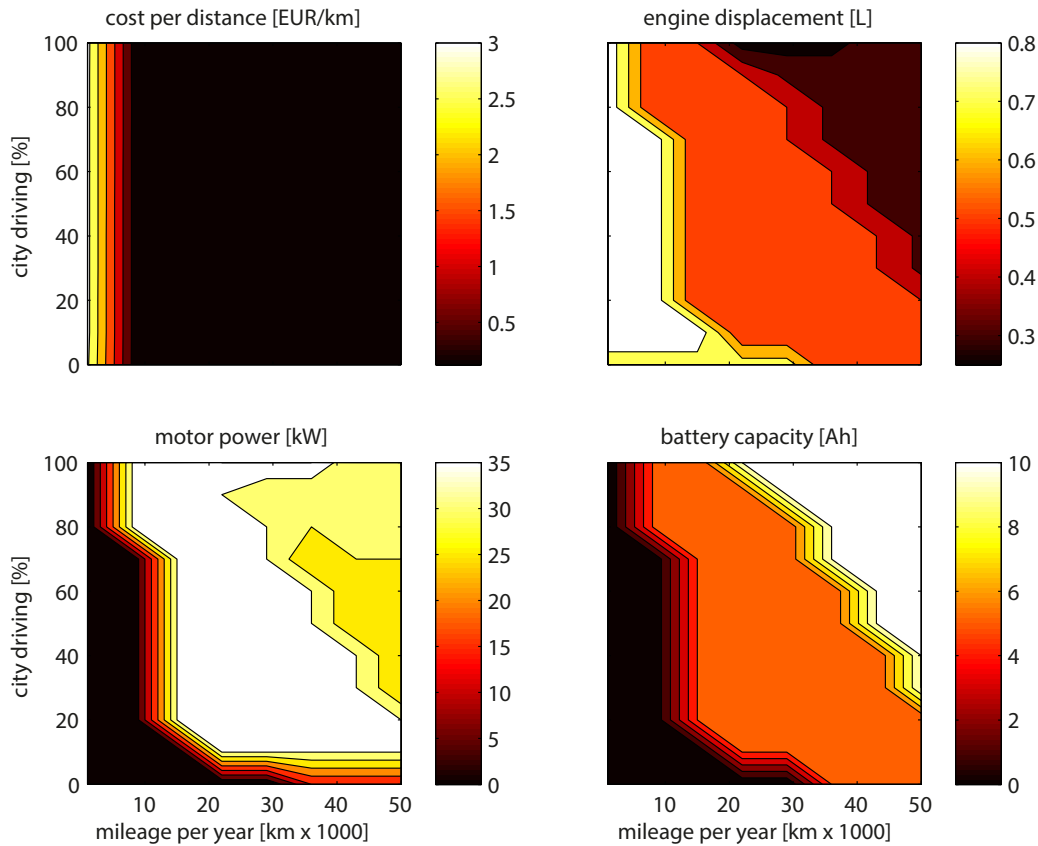


Fig. 6: Optimum cost and size as a function of mileage and city driving contribution during vehicle life time. Calculated with driver A routes.

in city operation, highway driving may considerably displace the optimum to another sizes combination and fuel economy as well. There are two reasons for this behavior: on one hand, highway cycles were completely different from each other, since driver A drove at a constant speed –little chance to recover energy and reduced electrical path size– and driver B kept accelerating and braking; on the other hand, intuitively, fuel efficiency may significantly vary from city to highway operation due to their different nature.

Highway driving usually means higher and constant power requirements. Since energy comes ultimately from fuel, the engine must fulfill the increased average power requirement. Consequently, since requirements are more homogeneous over the time, there is less opportunity to buffer energy on the battery, so the electric path is reduced. These influences may be appreciated in 5 as motor and battery are quite reduced in highway operation. Anyway, the same philosophy could be followed to evaluate any kind of driving cycle: on one hand the higher the power requirement, the bigger the engine; on the other hand the more homogeneous the demand is, the smaller the motor and battery are.

Since route type significantly affects the solution of the problem, its impact on optimal powertrain size is analyzed more deeply. A parametric study was done varying the weight of city and highway driving along HEV life time, expressed as the fraction of city operation. Thus, a set of artificial driving cycles were built by concatenating real city and highway driving cycles from driver A in a random order with the specified weights, using 50 individual cycles to replicate a longer horizon (about one month of use). Of course, due to the increased cycle length, the discretization of the optimization grid had to

be downgraded to the values on table II; however, on a second approach the grid was restored to values at table I on the surroundings of the optimum. The results of the long term optimization are presented in figure 6, expressed with a set of optimum size surfaces as a function of mileage and city driving fraction.

Operation costs slightly change with route type: due to the low sensitivity of motor and battery selection, the engine is the only machine that grows with highway cycles, resulting in a worse fuel efficiency (4.59 versus 4.13 L/100 km for the 30,000 km/year mileage optimum solution) but a cheaper vehicle due to the reduced motor and battery pack (31,393 versus 32,294 EUR). However, since those differences are quite small, in a long term evaluation the total operation costs are not very different as it may be appreciated in figure 5.

The non-hybrid zone may be appreciated on the left-bottom area of plots in figure 6. The area gets narrow when increasing city contribution since hybridizing the vehicle is more attractive for economy. The small zone at the bottom of upper right plot where a different engine is used means that there is a displacement that fulfills highway but not city cycle. The engine size decreases as the mileage increases as well as the city driving contribution, reaching the smallest displacement on highly city driving.

Battery follows a similar scheme. Rightwards from non-hybrid zone (where battery capacity is null) the size increases rapidly as the engine displacement decreases. The increased capacity with city contribution trend is quite the same.

The motor size trade-off is not so clear because it is a relatively cheap machine that could be redeemed easily, so its selection depends mostly on its efficiency and coupling with battery (as previously commented). Thus, on the boundaries highway driving requires a small motor, while city cycles use to have a greater chance to recover energy, so motor and battery should be bigger. On the mid area, at low mileages, the vehicle required a big motor to run a larger displacement engine at high efficiency levels, mostly during city driving; as engine displacement decreases with mileage the electric motor size is also reduced.

V. CONCLUSIONS

The present work introduced a structured methodology to optimally select the appropriate size for the different components of a hybrid electric vehicle for a given type of use (i.e. driving cycle, mileage, etc.). For a particular aim, any kind of multipurpose target could be also defined.

This task is performed evaluating the fuel consumption for a set of possible powertrain sizes. A scalable model has been developed for simulation purposes, being possible to resize engine, motor and battery as desired (where performance, weight and price are also consequently updated). The HEV control strategy is individually optimized with dynamic programming. Then, a 3-dimensional space of solutions is generated for a given driving cycle, where each engine, motor and battery triplet implies a fuel consumption and vehicle purchase price. The space of solutions may be used as a baseline to calculate the optimum under different situations.

A Pareto frontier analysis shown that fuel economy is almost insensitive to variations on motor and battery size above a certain limit. That limit is defined on the motor side by the aggressiveness of the driver, while on the battery side is defined by the maximum quantity of energy that can be buffered along the cycle; however, the optimal battery size usually is related to the motor size, since it defines how much power could be recovered. Thus, the optimal fuel economy is achieved by reducing the

engine size close to the infeasibility boundary, increasing motor size to the turning point limit and enlarging battery capacity accordingly.

Considering not only the efficiency of the vehicle but also the purchase price in the optimization, a trade-off that expresses the cost and optimal sizes for different amounts of use may be calculated (or equivalently, mileage for a 10 years vehicle life time). Thus, for a particular type of use and a mileage per year, the HEV powertrain size that minimizes the total cost is obtained. In the limit, for a null mileage the best option is the cheapest car (usually a non-hybrid since non plug-in technology is considered in this study) while for infinite mileage it is the most efficient powertrain. Due to the high fuel saving with the optimum HEV, this configuration is easily redeemed for city driving at a relatively low mileage (from 5,000 to 10,000 kilometers per year); however, since the non-hybrid vehicle is more efficient on highway, the fuel economy advantage is reduced and, therefore, the redeeming mileage increases to about 40,000 kilometers per year, confirming that a HEV is much more attractive for city driving as expected.

Different drivers did not show significative differences in optimal size for a particular type of route. Only the aggressiveness of the driver style slightly displaces the optimal motor size to couple with the maximum power requirement of the cycle while maintaining the engine displacement as low as possible. Nevertheless, route type (i.e. city or highway) supposes a great difference in optimization results. Apart of the differences in the redeeming horizon commented so far, highway operation requires a bigger engine and smaller motor and battery.

Finally a parametric study on the optimal size varying the amount of city driving over the HEV life time was performed. It showed that up to approximately 5,000 kilometers per year the optimal size is a non-hybrid vehicle for any city driving fraction. Above 35,000 kilometers per year the solution tends to be the most efficient HEV at any situation. However, in between the size significantly depends on the amount of city driving performed.

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