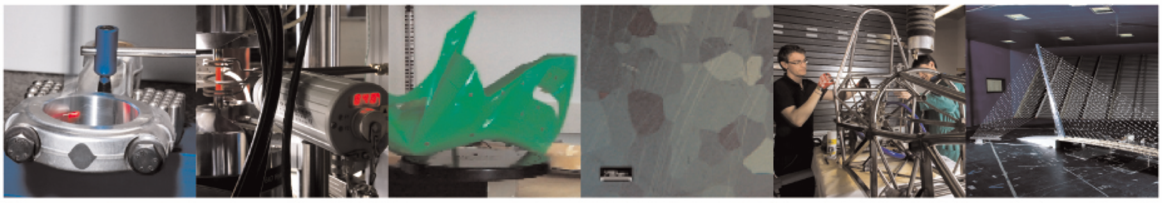

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Original article

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Multi-objective vehicle optimization: comparison of combustion engine, hybrid and electric powertrains

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Abstract

The use of optimization techniques has been extensively adopted in vehicle design and with the increasing system's complexity, especially with the introduction of new technologies, it plays an even more significant role. Market competition, stringent mandatory emission regulations and the need for a future sustainable mobility have raised questions over conventional vehicles and are pushing towards new cleaner and eco-friendly solutions. Fulfilling this target without sacrificing the other vehicle's requirements leads to extremely challenging tasks for the vehicle's designers. The use of virtual prototyping emerges as a possible breakthrough allowing to rapidly assess the effect of design changes and the impact of new technologies. The study presented in this work provides a suitable approach to compare different vehicle powertrain architectures through optimization techniques and deploying model-based simulation to rapidly assess vehicle performances. The vehicle model is defined at the components level through scalable models obtained from based on detailed simulation. An optimal energy management is applied to the power sources and transmission gear shifting. The optimization technique consider the main design variables of the various components including vehicle chassis and extensively exploits the design space. The multi-objective optimization considers vehicle's consumption, emission, range, longitudinal and lateral dynamics, costs and further performances to comprehensively assess the vehicle. The results allow to compare four different powertrain architectures: combustion engine vehicle, hybrid electric vehicle with parallel and series configuration, and battery electric vehicle. The results allows furthermore to identify technological limitations and conflicts among the different objectives. A critical analysis over the main design variables allows to identify the more suitable values and in particular, for combustion engine, gearbox and electric traction drive detailed comparisons are provided.

Keywords

Vehicle design, multi-objective optimization, genetic algorithm, powertrain, combustion engine vehicle, hybrid electric vehicle, electric vehicle, energy consumption, costs, vehicle dynamics.

Introduction

The demand for sustainable and environmental friendly mobility is putting pressure on automotive industry towards more energy efficient and cleaner vehicles. Current internal combustion vehicle (ICEV) architectures are stressed out at all levels, from individual components to the entire system management, in order to achieve enhancements. Technological barriers appear to shrink eventually significant advances and therefore new solutions are increasingly taking hold, in particular the addition or even the replacement of some standard components and parts through electric equivalent ones rise as a promising solution. Electric vehicles (EV) best fit the future sight of "eco-cities" by means of zero-pollution mobility, however major concerns emerge regarding charging infrastructures, energy availability from renewable sources, battery recycling and customer range anxiety. The latter finds a compromise solution through hybrid electric vehicles (HEV) which by coupling combustion engine with and electric traction system afford acceptable vehicle's range without sacrificing tailpipe emission reduction. The major drawbacks involve system complexity and costs increase. The identification of the most suitable configuration and the search for an optimal design require a deep understanding of the individual components and the mutual interactions. This task is made furthermore challenging and ambitious since the vehicle design must comply with a multitude of further aspects concerning customer satisfaction: driveability, safety, cost, comfort, etc. Nevertheless the final "product" has to be feasible and profitable for the company and satisfy a variety of standards and regulations.

In this context, decision-making becomes crucial already at the very early phase of vehicle design. Nowadays, this aim is pursued more and more extensively through Computer-Aided-Engineering (CAE) coupled with appropriate optimization techniques. Development time and expensive prototypes production are lessened, failures and impracticable designs can be detected and immediately put aside, different solutions can be rapidly tested and progresses are more easily achievable. Although shining as an extremely appealing and "win-win" approach, many difficulties are encountered in order to follow successfully this path. The realization of appropriate models is crucial, they must be able to provide reliable and accurate results, however a trade-off between accuracy and computational cost is generally necessary. The models represent the tool to observe the impact of the design variables on the vehicle's performances, still a suitable method is needed to navigate through the countless possible combination of design variables to reach the set that ensures the optimal vehicle's performances. Furthermore, vehicle design involves a myriad of objectives and therefore the search is more precisely not addressed to a single optimal solution but rather to a set of solutions which in general result from conflicting objectives. The choice of the optimization technique is therefore also crucial. The best solution have to be reached with good accuracy but at the same time good "exploration" capabilities of the design space are required. The adopted algorithm must be able to handle design variables which can be discrete or even non-numeric and to deal with multiple objectives. Multi-objective optimization has gained more and more relevance during last decades and various methods have been developed to handle such problems.

Even though the literature is rich of contributions regarding the study, modeling and optimization of vehicle components and subsystems only few works target at the whole system and even so only a very limited set of objectives are taken into account.

The most common approach for complex systems design is based on the decomposition of the system into its subsystems and furthermore to its components, in a cascade manner up to the desired level of detail. A comprehensive approach is proposed by Ford [1], other references can be found in aerospace industry as shown by Airbus [2]. Similar approaches are employed for the car body design by Daimler [3], BMW [4] and Ford [5], gear shifting strategy [6], air conditioning system [7] and active suspension [8].

Application to specific powertrain layouts are provided for ICEV [9,10], HEV [11,12] and BEV [13] where for the works regarding HEV and EV scalable approaches are applied for the powertrain's components definition in order to handle design variations. A method for developing scalable models of the combustion engine and the electric motor can be found in [14] and further techniques referring to data mining are described in detail in [15].

Multi-objective optimization techniques are a major topic in last decades and therefore innumerable references can be found in the literature, the most used techniques and detailed illustration of the algorithms are presented in [16,17,18]. Evolutionary algorithms and in particular genetic algorithms have been increasingly popular for solving multi-objective optimization and many different formulation has been proposed in [19,20,21,22].

Vehicle model

The vehicle model section is divided in two parts. In the first part the different components used to build the models are described, in particular the concept of scalable models is presented for the individual components. Particular emphasis is given to description of the physical behavior of the components. The second part provides an illustration of the procedure used to define the entire vehicle system and the system models adopted for the different simulations.

Components models

The components models provide the physical behavior, costs and mass of the individual components. In this work emphasis is given to the description of the physical models while references regarding models or data for estimating mass and costs are cited. The physical models are developed in order to provide a trade-off between accuracy and computational cost. This purpose is achieved by a procedure of data mining where a set of results from detailed models are fed to the algorithm to generate simplified models. The set of results regarding the individual components originate from a previous work [23]: the internal combustion engine (ICE) model is based on 1D-CFD simulation using the commercial software WAVE® from Ricardo coupled with detailed formulation to take into account the mechanical losses [24]; the electric motor (EM) model benefits from 2D electromagnetic FEM capabilities offered by the commercial software Motor-CAD® [25] allowing a detailed description of the motor's geometry and materials properties; the inverter model uses data from Infineon [26]; the battery model is based on Panasonic 18650 data [27]; the transmission is developed in the commercial software Dymola® and relies on a detailed description of the components by using data and models from FZG [28,29] and SKF [30]; the chassis and vehicle's body properties are defined through parametric formulations based on data from real-world vehicles.

The battery and inverter models are quite simple and therefore only marginal simplification are introduced to streamline the models computation: an average operating temperature of the components is used and for the battery a constant ohmic resistance is used to define the equivalent battery's electrical circuit. The battery cost is based on the studies in [31,32].

A more intense process of data mining is employed for the ICE, the EM and the transmission through scalable models based on reference data. Other approaches can be found in [33,34,14].

The ICE results derive from a set of engines used in vehicles recently on the market [35], the range covered by the main design variables is listed in Table 1.

Table 1. Engine data statistics (Values range)

Parameter	*Min*	*Max*
Bore [mm]	70.8	98
Stroke [mm]	69.9	97
Compression Ratio [-]	8.7	12
Number of Cylinders [-]	3	8
Displacement [l]	1	5.6
Number of Engines	87	

The scalable ICE model developed uses the results of a specific engine as reference values and then through mathematical formulations depending on the main design variables the effect of design variations on the engine's performances is taken into account [23].

The reference engine is based on data from the Volkswagen EA211 TSI EVO [36], the results and the comparison with the real-data are shown in Figure 1. The efficiency map is available only for the EA211 96 kW which operates with a turbo providing a lower pressure boost, the simulated model benefits from a higher pressure boost (1.2 bar) so that the maximum power is closer to the EA211 110 kW version using a 1.3 pressure boost [37].

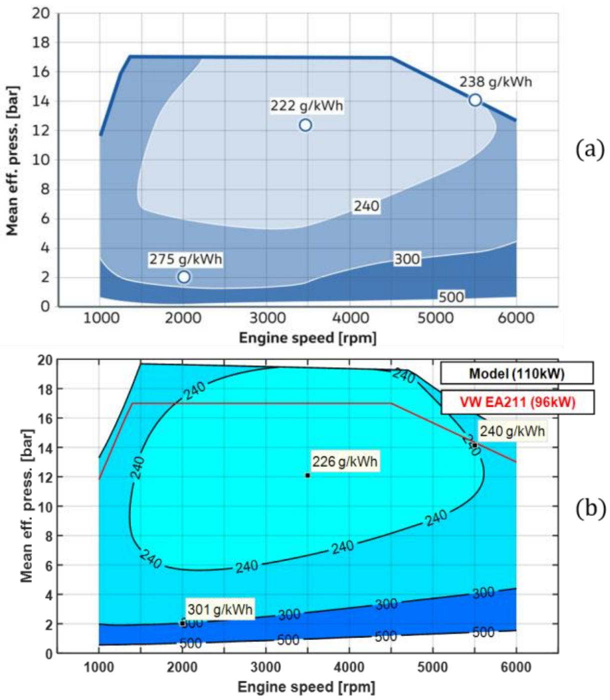

Figure 1. Engine BSFC comparison: real data (a) vs simulation results (b)

The design variations are obtained by scaling the reference model, this procedure is applied to the maximum torque, T_{max}, the pumping torque, T_{pump}, the mechanical friction, which considers two contributions respectively the oil dependent term, $Fric_{Oil}$, and the constant term, $Fric_{Cnst}$, and the brake specific fuel consumption, *BSFC*. The torque and friction quantities are all normalised by the engine displacement, V_d. The same mathematical formulation is applied to all these quantities and the dependency on the main engine design variables is introduced in a power low form as shown in equation (1).

$$\varphi_{ICE} = k_0 + k_1 Cyl^a CR^b B^c S^d \qquad (1)$$

The function φ_{ICE} provides the scaling coefficient to apply in order to determine the generic scaled quantity, ψ_{ICE}, (normalised maximum, pumping and friction torques, and *BSFC*) with respect to the reference quantity by $\psi_{ICE} = \psi_{ICE,ref}(\varphi_{ICE}/\varphi_{ICE,ref})$, k_0 and k_1 are constant coefficients, *a*, *b*, *c* and *d* are the exponents to be identified and that express the dependency of respectively the number of cylinders, *Cyl*, the compression ratio, *CR*, the bore, *B*, and the stroke, *S*.
The parameters are identified by solving a mean square error minimization problem and the results are presented with a linear correlation value to indicate the accuracy. The results are generally extremely accurate, the major error occurs at the pumping torque which contribution is however relevant only at very low loads. Nevertheless, improvements in accuracy could be obtained by fitting separately the scaling model coefficient to the various engine models according to the number of cylinders.

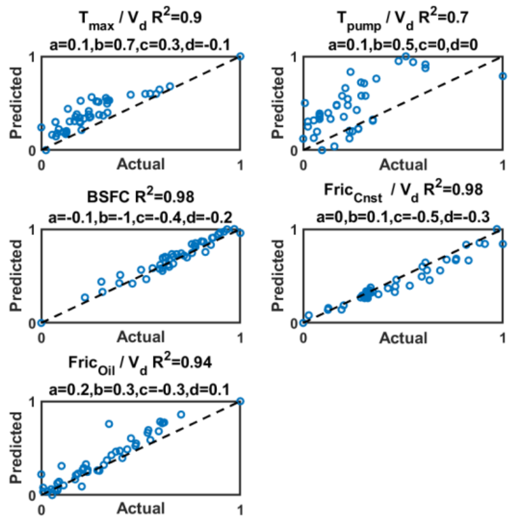

Figure 2. ICE scalable model: parameter identification comparing actual values and predicted values

The engine mass is estimated depending on the main design parameters and reference values can be found in [38,39,40] while costs are based on [41,32].

A similar approach is applied for the electric motors by considering both Permanent Magnet Synchronous Motors (PMSM) and Asynchronous Induction Motors (AIM). The reference models are respectively the BMW i3 and TESLA Model S motors for which data, models and results validation can be found in [42]. The set of electric motors results was developed in [23] and the scaling formulation depends on the motor mass, m_{EM}, the peak current, I_{pk}, and peak voltage, V_{pk} as presented in equation (2).

$$\varphi_{EM} = k_0 + k_1 {V_{pk}}^a {I_{pk}}^b {m_{EM}}^c \qquad (2)$$

The quantities scaled are respectively the efficiency, maximum torque and nominal speed while the coefficient values are reported in Table 2. Voltage and current maps are scaled according to peak voltage and peak current while power factor is scaled to match the efficiency.

Table 2. Electric motors scaling coefficients

	Coefficient	PMSM	AIM
Efficiency	a	0	0
	b	0	-0.1
	c	0.1	0.2
Max Torque	a	0	0
	b	0.9	0.6
	c	0.7	0.8
Nominal Speed	a	1	1
	b	-0.3	-0.2
	c	-0.6	-0.3

The correlation value is generally above 0.99, this is due to the scaling procedure used to generate the electric motor result database in the previous work [23]. Nevertheless, it should be noticed that the mass quantity is dependent on the peak current since a maximum current density should not be exceeded to preserve the coils integrity.
The motor costs are defined according to [41,32] where specific costs are assigned respectively to PMSM and AIM motors and power electronics costs are included. The electric motor mass is calculated directly based on the physical model of the motor realized in [23].

The physical behavior of the individual transmission components, gearbox and differential, is defined through a simple equation expressing the power loss occurring at the component.

$$P_{loss} = -(1-\eta_t)P_{in} - k_t\left(\frac{N_{in}}{1000}\right)^{m_t} \qquad (3)$$

The power loss, P_{loss}, depends on the input power, P_{in}, and input speed, N_{in}, while the coefficients, η_t, k_t, and m_t are obtaining from a fitting procedure of results from detailed transmission models [23].
The transmission cost and mass are estimated based on [41] and manufacturer's data [43,44].

The tire model uses a simplified formulation allowing to assess vehicle's longitudinal and lateral dynamics. The parameters used are the maximum friction in tire-ground contact, rolling resistance coefficient based on standard values and scaled according to maximum friction [45,46,47] and cornering stiffness depending on vertical load [48] and tire geometry data from manufacturers [49].

The vehicle's body frame introduces an additional inertia in the vehicle definition and the mass is evaluated depending on the vehicle's length and height [50]. The possibility of using innovative materials to reduce weight is taken into account by a percentage lightweight parameter applied to the nominal body's weight and determining an increase in the body's cost according to [51].

System models

The model of the entire vehicle is obtained by coupling together the different components through physical connections. Four different configurations are analysed in this work: conventional combustion engine vehicle (ICEV), hybrid electric vehicle with parallel (HEVp) and series (HEVs) layout and battery electric vehicle (BEV). A schematic representation of the layouts it's shown in Figure 3.

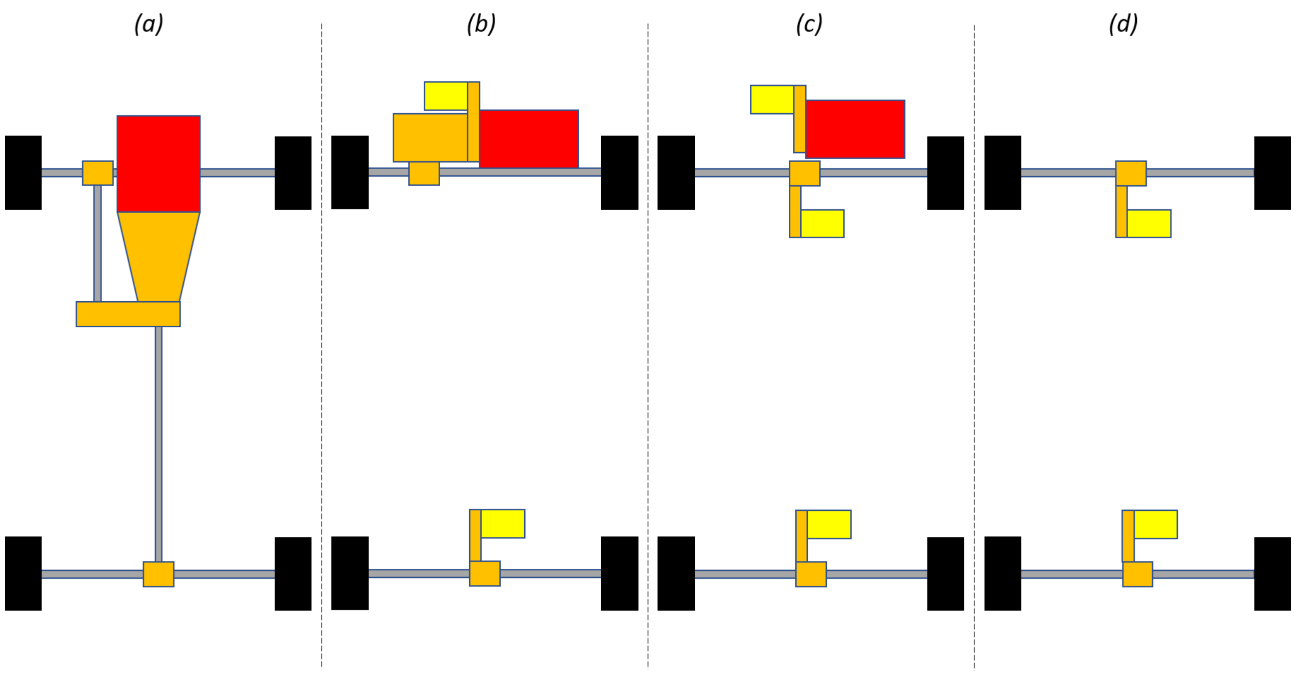

Figure 3. Vehicle layouts: ICEV (a), HEVp (b), HEVs (c) and BEV (d) (red: combustion engine, yellow: electric motor, orange: gear components)

The system generally still requires the definition of an appropriate control strategy to manage various aspects like gear shifting and power split among the different traction units.
The procedure is based on comparing efficiency maps and identifying the control strategy that maximise the energy efficiency.

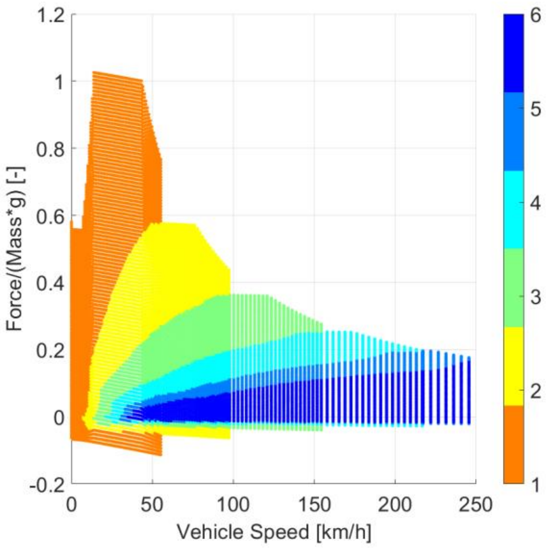

Figure 4. Gear shifting control strategy for 6-speed ICE gearbox

The gear shifting scheduling is obtained by evaluating and minimising the power losses across the gearbox for all possible gear configurations with constraints applied to the minimum and maximum speed provided by the specific gear considered.
Examples of the resulting control strategies for a 6-speed ICE gearbox and a 2-speed electric motor (EM) gearbox are respectively provided in Figure 4 and in Figure 5.

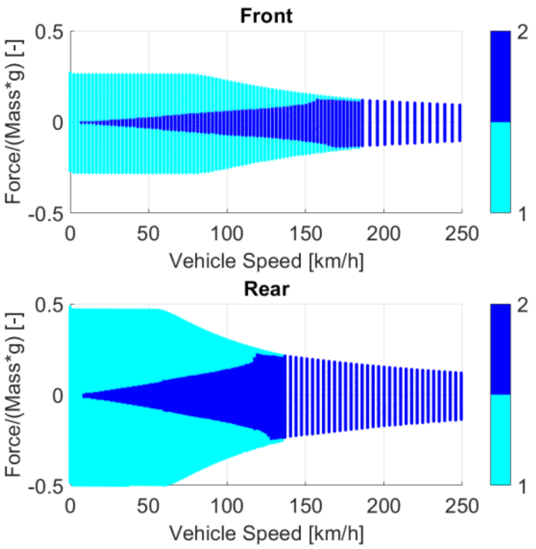

Figure 5. Gear shifting control strategy for 2-speed EM gearbox front and rear

The power split control management applies to both the load repartition among the front and rear electric motors in HEV and BEV and the power flow between the combustion engine and electric motor in HEV.
The power split strategy between the electric motors differs with respect to traction and braking conditions: in the first case an energy consumption minimization strategy is applied while in the latter a vertical load transfer dependent repartition is applied. An example of power split map with respect to vehicle speed and acceleration is shown in Figure 6.

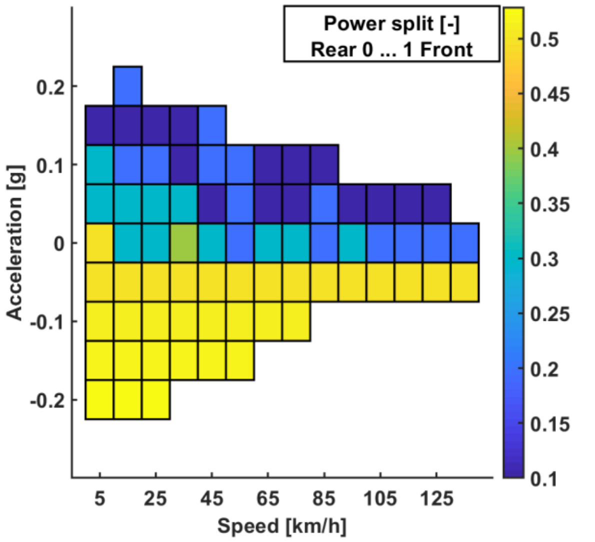

Figure 6. Power split between front (130 kW) and rear (190 kW) electric motor in WLTP driving cycle

In HEV two strategies are applied depending on the operating mode. The boosting mode is defined so that pollutant is minimised and therefore the ICE is used only when the power demand exceeds the maximum power provided by the EM. The recharging mode represents the situation where the ICE is used to recharge the battery and so the EM acts as a brake and in this condition the power split between ICE and EM is obtained by minimizing the ratio between the output power and fuel power. The output power in case of parallel HEV (HEVp) is the sum of the power to the battery and the power delivered to the wheels while in case of series HEV (HEVs) equals the power to the battery. In both cases it is possible to operate the ICE at higher efficiency. In terms of architecture design, it is worth noticing that in HEVp the EM provides both traction and braking while in HEVs the EM used to recharge the battery is generally referred to as generator (GEN) since its purpose is to draw current from the mechanical power of the ICE.

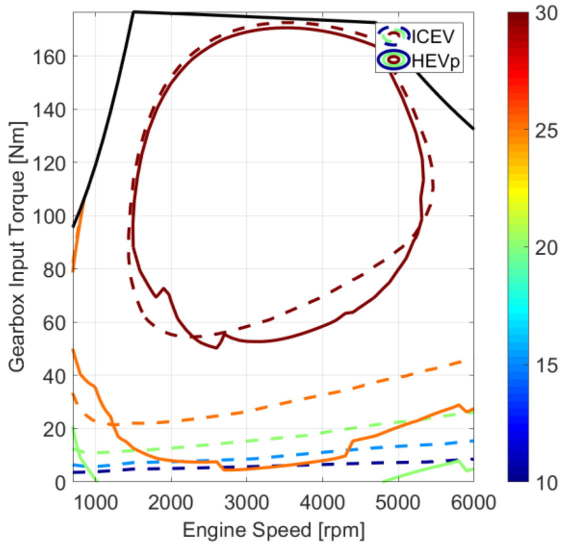

Figure 7. Comparison of ICE efficiency maps: ICEV vs HEVp

For the HEVp the matching procedure between ICE and EM is realized over the entire map, since the ICE provides directly propulsion to the wheels all the possible operating condition can be reached. Figure 7 shows the effect of introducing an EM and applying the ICE-EM matching procedure. The output torque refers to the torque transmitted to the gearbox, the torque absorbed by the EM allows to operate the ICE at higher torque and therefore higher efficiency while providing the same torque to the gearbox and the advantage is particularly remarkable at low loads.
For the HEVs the decoupling between ICE and wheels is taken advantage so that the ICE working conditions are limited to a reduced set of optimally efficient points.
An example is provided in Figure 8, the optimal set, black points, is obtained through a direct search method starting from the minimum load and speed condition. The optimal matching, yellow point, identifies the working conditions at which the matching provides the maximum efficiency. The recharging mode is therefore applied to the

vehicle in order to optimally benefit from this matching. The optimal matching condition is applied for most of the vehicle's driving situations. This is obtained by regulating the share of the current to the battery with respect to that directly provided to the traction motors. Table 3 provides a summary of the procedures used to define the control strategy. For the HEV only the matching procedure regarding the recharging mode is reported since the boosting mode uses a simpler strategy. The vehicle is driven purely electric unless the load condition exceeds the EM power and in that case the ICE is activated and covers the overloading. This solution is adopted with the intention to minimise the emissions in this operating mode.

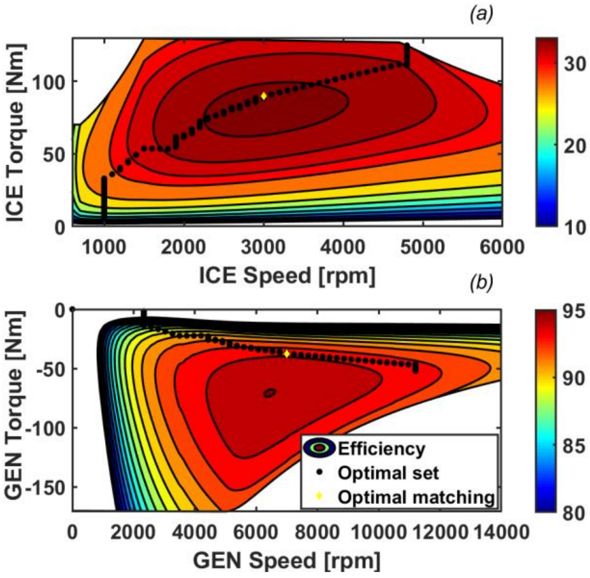

Figure 8. ICE (a) and GEN (b) matching in HEVs

Table 3. Control strategy evaluation

Gearbox
• calculate the power loss contributions from the components between the energy source and the gearbox and obtain the overall power loss, P_{loss}, • for *i* = 1:number of gears • calculate power loss across gearbox (equation 3) and add this contribution to P_{loss}, • calculate the gearbox output torque and speed and detect the range overlapping with the values obtained by using the previous gear, • compare the P_{loss} of the current and previous gear, • for each gearbox output torque and speed select the gear that minimises the P_{loss}.
Power split (Electric motors)
• defined at the vehicle level, • definition of a set of possible load distribution between front and rear axle (0:0.05:1), • for each load distribution select the load distribution value that minimises the energy consumption.
ICE-EM matching (Hybrid)
HEVp: for each gearbox input speed and torque, $P_{Gearbox}$, (depending on ICE maximum torque curve) calculates the EM load, P_{EM}, to maximise the energy conversion, η_p. $\eta_p = \frac{P_{Gearbox} - P_{Battery}(P_{EM})}{P_{Fuel}(P_{EM})}$ $(P_{Battery} < 0, during\ recharging)$ HEVs: • starting from the ICE minimum speed and torque the operating points are detected by a step-by-step procedure maximizing $\frac{\partial \eta_s}{\partial P_{ICE}}$ with $\eta_s = \frac{i_{DC}}{P_{fuel}}$ and i_{DC} corresponding to the current draw from the generator's inverter. This current is used both to recharge the battery and provide vehicle traction, the actual repartition is evaluate according to the load condition and the battery efficiency.

The last step in the modeling phase involves the definition of the models to be used to eventually assess the vehicle performances. The models are chosen according to the specific simulations as a trade-off between accuracy and computational cost. The vehicle's simulations mainly involve energy consumption and dynamics evaluation.

A rigid body with 2 degree of freedom (d.o.f.) model is applied to describe the longitudinal dynamics of the vehicle [52]. It considers a straight road driving condition and takes into account the vertical load transfer between the front and the rear axle according to acceleration and geometrical properties. The tire slip is neglected while the maximum force transmitted to the ground is limited by the tire's friction coefficient. This model is applied to simulations regarding consumer's driving cycle, specifically the Worldwide harmonized Light vehicles Test Procedure (WLTP), straight road acceleration and top speed assessment and slope road climbing.

The WLTP assessment is reduced to a set of point to reduce the computational time. Therefore, it is not required to simulate the entire driving cycle of 1800 s but rather a limited set of condition whose influence is defined through a statistical analysis over the driving cycle as shown in Figure 9.

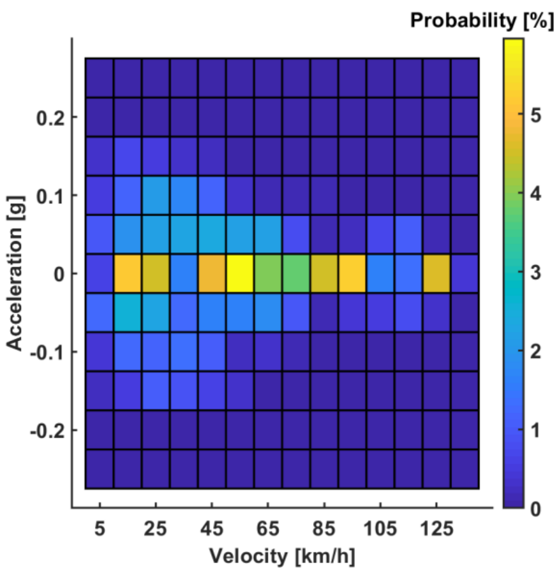

Figure 9. WLTP drive cycle statistical analysis

The vehicle's lateral dynamics is based on the single-track model [53] which describes the vehicle motion with respect in-plane velocity, yaw and side slip angle. Steady-state cornering and step steering input are evaluated through this model.

Optimization

The optimization procedure requires the problem definition and the choice of the solution technique.

The problem formulation provides the list of design variables, objectives and constraints.

The design variables set contains the major parameters of the various vehicle components. The variables are defined respectively as allowed values or by upper and lower boundary values. Table 4 lists all the inputs used to initialize the model, allowable values and boundaries are reported for the design variables. The body and tire constant parameters refers to average values for class D vehicles (Audi A4, BMW series 3, Mercedes C-Class). All-wheel drive (AWD) layout is considered since it generally allows to improve vehicle traction and for EM propelled vehicles it allows to optimally distribute the power flow between front and rear axle to minimise the energy consumption and increases regeneration capabilities. The scaling factor applied to the battery represent a technological degree of freedom in terms of battery's power density. The scaling factor, SF_{batt}, applies to battery's mass and cost respectively proportionally to $\sim 1/(1+SF_{batt})$ and to $\sim 1+SF_{batt}$. The GEN current is defined as a ratio of the battery current. Manual (MT), dual-clutch (DCT) and automatic (AT) transmissions are used for the gearbox connected to the ICE and number of gears are defined as difference values to be summed up to common minimum values, respectively 5, 6 and 7. The gearbox progression factor is a value that defines the "shape" of the gear ratios in between the maximum and minimum gear ratio [54]. A low value provides a solution similar to a geometric design while higher values return a progressive design. The EM gearbox design is simplified in order to reduce the number of design variables. The maximum gear ratio of the front gearbox is defined and by matching the maximum speed of the front and rear motors the gear ratio on the rear gearbox is evaluated. In case of 2-speed gearbox the second gear ratio is defines halving the maximum gear ratio. The same differential is applied to front and rear axle and the gear ratio is defined as a ratio of the maximum gear ratio of the ICE gearbox for ICEV and HEVp and of the front EM gearbox for HEVs and EV.

Table 4. Model initialization design inputs

[1]Body	*Length [mm]*	4700	**[5]ICE**	*Bore/Stroke*	0.8,…,1.2
	Height [mm]	1440		*CR*	9,…,13
	Cd	0.29		*Bore [mm]*	65,…,100
	Lightweight [%]	0,5,10		*Cylinders*	3,4,6,8 (3,4**)
[2]Tire	*Radius [mm]*	328	**[6]EM([7]GEN)**	*Type*	PMSM,AIM
	Friction	0.8,1,1.2		*Current ratio (GEN/Battery)*	0,…,2
[3a,3b]Layout	*Driving mode*	AWD		*GEN speed [rpm]*	10000,…,20000
	[3a]One motor per wheel	y/n		*EMF speed [rpm]*	10000,…,20000
	[3b]Power distribution (rear/front)	0.1-0.9		*EMR speed [rpm]*	10000,…,20000
[4]Battery	*Series cells*	30,…,160(120*)	**[8]Gearbox^{ICE}**	*Gears add*	0,1,2
	Parallel cells	10,…,70(50*)		*Max gear ratio*	3,…,5
	Scaling factor	0,…,1		*Min gear ratio*	0.4,…,0.9
(*) HEVp, (**) HEVs				*type*	MT,DCT,AT
	Design variables			*Progression factor*	0,…,1
ICEV	1, 2, 5, 8,10		**[9]Gearbox^{EM}**	*Max gear ratio*	2,…,4
HEVp	1, 2, 3b,4, 5, 6, 8, 9, 10			*Front gears*	1,2
HEVs	1, 2, 3b, 4, 5, 6, 7, 9, 10			*Rear gears*	1,2
EV	1, 2, 3a, 3b, 4, 6, 9, 10		**[10]Differential**	*Scaled gear ratio*	0.5,…,1.5

The objectives consider the most relevant indicators representing the vehicle. In order to have a reduce set that doesn't "overload" the optimization search some objectives are either combined into an averaging term or introduced as constraints. The list of the vehicle objectives and constraints is presented in Table 5.

A geometric mean calculation, $\sqrt[1/n]{\prod_{i=1,n} p_i}$, is used for objectives with multiple performance indicators, p, and the individual indicator are normalized by physical or assumed minimum and maximum values, see Table 5. The objectives definition yields to a maximization search.

The consumption is evaluated as the cost of the primary energy sources, respectively 1.5 €/l cost of fuel and 0.2 €/kWh cost of electricity are considered. The emission is directly related to the fuel consumption and by data collection from automotive manufacturers a correlation value of 2.31 kgCO_2/l with standard deviation of 0.03 kgCO_2/l has been estimated. The emission objective is defined as a ratio with respect to the upcoming future European regulation [55]. The dynamics considers 0-100 km/h acceleration, top speed and step steering cornering maneuver performances and the overtaking results from 30-50,70-90 and 110-130 km/h acceleration times. The consumer objective expresses the level of achievement of the various vehicle performances of interesting for the consumer. Some of the previous objectives are used but their values are normalized with respect to common class D vehicles, off-road driving capabilities refers to driving condition in case of slope road, the cornering stability takes into account understeering or oversteering behavior of the vehicle at low lateral acceleration cornering and roll stability, the optional components installation assign additional points in case of components that can represent an added value to the vehicle like automatic transmission or one motor per wheel configurations. Off-road driving capabilities, cornering stability and optional components installation are not subjected to geometrical mean but rather summed up. The consumer objective is also used as constraint. Considering that a value of 50% fulfillment correspond to standard class D vehicle performances, a constraint value of 40% fulfillment “forces” the optimization strategy to look after design solutions where all variables achieve acceptable results and therefore avoid unrealistic designs.

The off-road driving capability is related to the maximum road slope that the vehicle is able to overcome. The under/oversteering behaviour is given by the wheel steer angle adjustment with respect to the Ackermann angle [52] to be applied during steady-state cornering at low speed and low lateral acceleration while the roll stability is simply given as the ratio between the center of gravity height and the vehicle width.

Table 5. Objectives and constraints

Objectives	***Simulation results [normalisation values: min-max]***	***Constraints***
Consumption	WLTP energy cost (fuel, electricity) [2–25 €/100km]	Maneuvers achieved
Range	WLTP range [0–600 km]	Minimum range
Emission	WLTP CO_2 emission, normalised value with respect to allowed emission according to regulation [0-200 %]	Minimum top speed
Dynamics [52,53]	0-100 km/h acceleration [2–14 s], top speed [140-300 km/h], peak yaw rate [0-20 %] and steering response delay [0-1 s]	Under/oversteering limitations
Overtaking	City [0.5-3 s], extra-urban [1-10 s] and highway [2-30 s] conditions	Climbing minimum road slope
Cost [41]	Vehicle overall cost [5-100 k€]	Consumer
Consumer	Average consumer satisfaction based on: objectives fulfillment of common vehicle performances, off-road driving capabilities, cornering stability and optional components installation $\text{Consumer} = \frac{1}{6}(\text{Consumption}[6\text{–}10\ €/100\text{km}] + \text{Range}[400\text{–}500\ \text{km}] + \text{Emission}[100\text{–}150\ \%] + \text{top speed}[250\text{–}300\ \text{km/h}] + 0\text{–}100\ \text{km/h acceleration}[3\text{–}5\ \text{s}] + \text{Dynamics}) + \text{optional components} \times 5\% + \text{off–road}[30\text{–}40\ \%] \times 5\% + \sqrt{\text{wheel steer angle}[\pm 10\text{–}0\ °] \times \text{roll stability}[0.1\text{–}0.5]} \times 5\%$	

The solution technique in this work uses an All-in-One (AiO) optimization strategy driven by a genetic algorithm (GA).

The AiO is the typical approach adopted for optimization problems, the procedure is based on a single level of optimization handling all objectives and constraints in a single problem. To solve complex problems it is possible to pursue more refined approaches. The problem can be decomposed into subsystem that are then solved separately and allowing in this way to parallelize those tasks. The major issue concerns the level of interaction between the subsystem and depending on that different decomposition strategy have been proposed [56].

The GA is a set of optimization algorithm belonging to the larger class of evolutionary algorithms (EA). Common applications of such algorithms occur in the topic of multi-objective optimization. The general algorithm common structure relies on bio-inspired species evolution to which mutation, crossover and selection operators are applied.

The Archive-based Micro Genetic Algorithm (AMGA) is used to perform the optimization. The algorithm [19] uses an archive to keep track of the search history and to store the best solutions allowing a faster convergence and a small population size.

Considerations on HEV optimisation

This section focuses on HEV and describes the motivations behind the settings adopted for the optimization of the parallel (HEVp) and series (HEVs) powertrain configuration and the calculation method used to evaluate the performances.

The study over HEVp and HEVs does not aim at an accurate comparison of the powertrain configurations but rather considers two different concepts of vehicle without exploiting the full design variables space. The HEVp is intended as an ICEV to which a limited amount of electrification is introduced while the HEVs is proposed as a BEV to which an ICE is added to work as range extender. This conceptual difference leads to the choice of restricting the space of design variables space. The battery pack of HEVp has a 25% reduced upper boundary value for both the number of parallel and series cells while for the HEVs only three and four-cylinder engines are allowed so that the respective maximum power is approximately halved.

A qualitative comparison between the two powertrain configurations is provided hereinafter. Considering the objectives used in this optimization and by allowing the configurations to fully exploit the design variable space, the HEVp would generally provide better performances compared to HEVs. For a given vehicle power, the dynamics mainly results in a similar behavior but HEVp shows a better consumption. By considering the two operating modes, boosting and recharging, different considerations can be made. Assuming a standard driving cycle, during boosting the traction is mainly provided by the electric motor, for a given maximum power the EM in the HEVs has to be of larger size compared to HEVp where the maximum power is achieved by the combination of EM and the ICE. Therefore, due to lower efficiency at partial loads of a larger EM the battery consumption increases. During recharging two power flows occurs, the one to recharge the battery and the other to provide traction. The flow to the battery is slightly more efficient in case of HEVs since the ICE can be regulated in both load and speed to optimally deliver energy while in HEVp the ICE speed follows kinematically the tire speed and the regulation is limited by the number of gears of the transmission. On the other hand, the flow to provide traction is far more efficient in HEVp since it must go through only the transmission while in HEVs the inverter and EM efficiency further increase the energy loss.

Nevertheless, focusing on components, the major difference lies on the reduction of mechanical components in HEVs (ICE gearbox) accompanied with an increase of electrical ones (GEN and its inverter). This scenario affects both costs and system’s reliability.

The optimization procedure used in this work uses a specific approach to evaluate range, consumption and emission in HEV. The WLTP is exploited in both modes, boosting and recharging. The first is mainly driven in pure electric mode while in the second recharging occurs. These results are combined in an optimization procedure to assess the most efficient utilization of the two modes complying with the constraint of maintaining a specific battery state of charge (SOC). The range evaluated in this calculation is then summed up to that in pure electric mode providing the overall vehicle's range. The fuel consumption and emission are scaled according to a reduction factor depending on the ratio between the electric and overall vehicle's range.

A further important aspect relates to the ability of the powertrain to reach all the points of the WLTP in both operating modes. In this work the fulfillment of such condition is introduced as a constraint and therefore both electric traction, in boosting mode, and ICE traction, in recharging mode, hence a minimum power is imposed to both accordingly to the maximum power required during the WLTP. This value varies accordingly to the vehicle characteristics but for a given value of power requested to ICE, P_{ICE}, or to the battery, P_{batt}, is possible to obtain then the power requested to the vehicle, P_{veh}, as function of the level of hybridization, LoH, in the range (0,1).

$$\begin{cases} P_{veh} = \dfrac{P_{batt}}{LoH} \\ P_{veh} = \dfrac{P_{ICE}}{1 - LoH} \\ LoH = \dfrac{P_{batt}}{P_{batt} + P_{ICE}} \end{cases} \quad (4)$$

Results

The results section provides an overview and a critical analysis over the solutions obtained by the optimization procedure.

Firstly, the optimal solutions are presented through the most relevant Pareto frontiers showing the conflict nature among various objectives and a comparison between the different design. The comparison is further provided with respect to an optimal solution, identified through a specific decision-making procedure, and some crucial physical indicators such as the CO_2 emission and the range.

The section ends with a critical analysis over the design variables' values and a sensitivity analysis by means of Pareto frontier for different design variables solutions.

Optimal solutions

The Pareto frontier identification of the different objectives allows to identify the best solutions achievable. By applying this procedure pair-wisely to the objectives is possible to clearly compare the different powertrain configurations. To provide a more extensive comparison, the obtained frontier is extended by considering additional solutions from the optimization. The results are shown in Figure 10. The ICEV allows the cheapest solutions but suffers from higher consumption and the maximum achievable dynamics is lower compared to the other configurations. The HEVp and HEVs locate mostly in the middle between ICEV and BEV considering cost, consumption and dynamics but prove to be generally the most effective solution towards consumer satisfaction. The HEVp allows better consumption and lower costs. The ability of the HEVs to reach higher maximum dynamics lies on the definition of battery design variables. Higher electric power is allowed in HEVs and hence the dynamic performance tends more closely to the results achieved with BEV. The BEV is characterized by strong improvements in dynamics and consumption but also of costs. The frontier extension is particularly noticeable in the cost-consumption and consumer-cost comparisons. In the first case it is possible to clearly detect the covered regions and therefore the limitations for the different powertrain configurations. In the second case it can be seen that the consumer objective achieves a peak value at a different vehicle's cost according to the specific powertrain adopted except for the BEV for which the conflicting behavior between the objectives covers the entirely showed range.

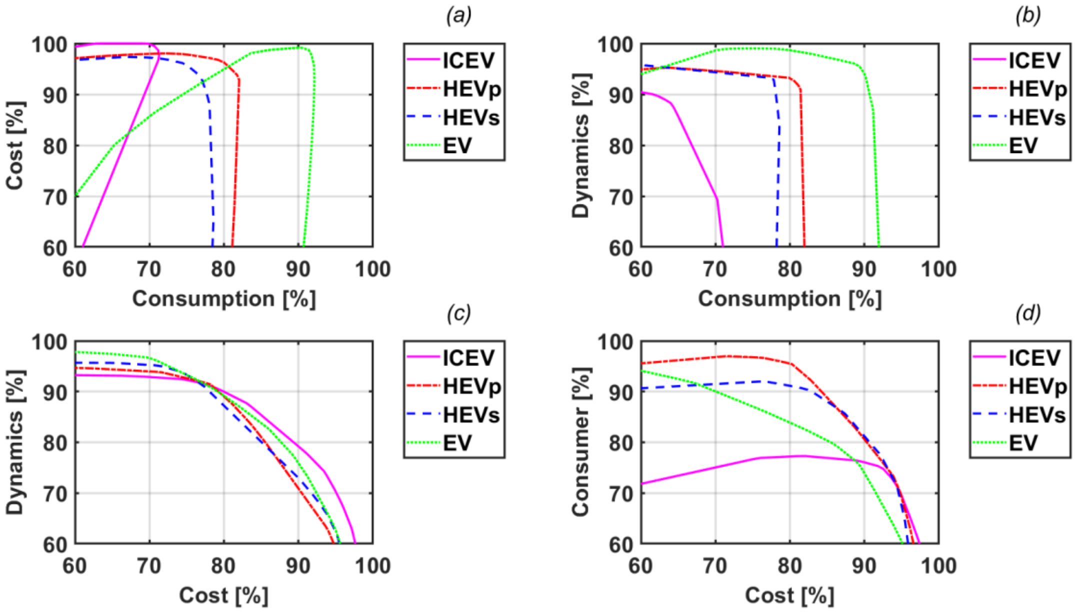

Figure 10. Pareto frontiers: cost-consumption (a), dynamics-consumption (b), dynamics-cost (c) and consumer-cost (d)

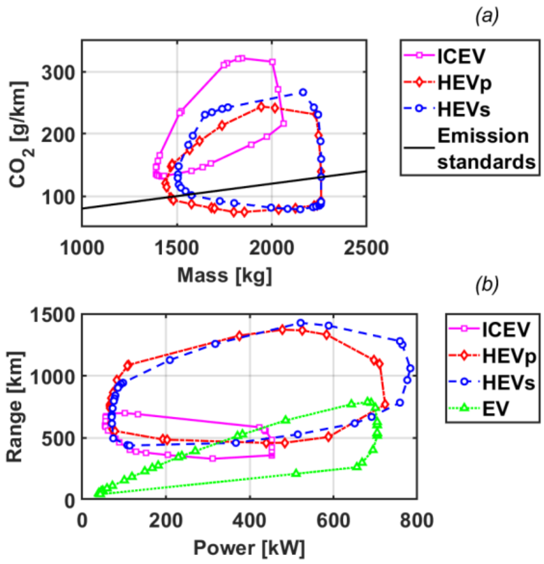

Figure 11. Specific vehicle performances: CO_2 emission vs vehicle mass (a) and range vs vehicle power (b)

The ICEV and BEV consumer values are generally limited since some key aspects cannot be satisfied. For ICEV this is mainly due to the emission regulation fulfillment while for BEV range appears as the most critical aspect. Emission regulation fulfillment and range comparison among the different powertrains are shown in Figure 11. With the current technology the ICEV is not able to fulfill emission standards while BEV provides a range comparable to ICEV only for high installed power.

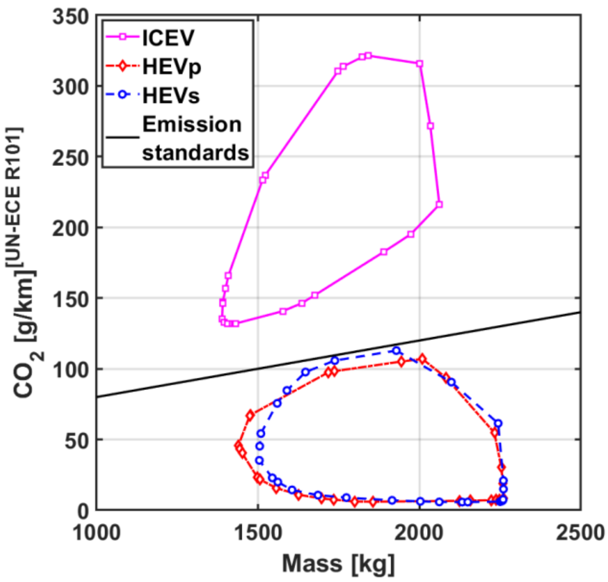

Figure 12. CO_2 emissions for ICEV, HEVp and HEVs calculated by using the UN ECE R101 formula

The emissions reduction through HEV is even more remarkable when applying the UN ECE R101 formulation for calculating the emissions

[57]. This technology is actually able to appreciably fulfill the current standards as shown in Figure 12. The difference with respect to the approach adopted in the optimisation mainly relies on the influence given to the driving range in the charge sustain operating mode. The optimisation considers the actual fuel tank range while the regulation sets a constant value of 25 km.

Another standard method to compare different optimization results is offered by spider graphs. In this way is possible to represent all the objectives together. Figure 13 provides the comparison between different optimal solution of the various powertrains. The solution is chosen by evaluating the minimum distance from the utopia point with a slight modification in the calculation procedure. The standard approach requires the normalization of the different objectives and the solution is selected according to the minimal Euclidean distance. In this case a slight modification is applied by scaling the objectives' individual distances. Since various objectives are considered, correlations among them might occur and therefore the search would be drifted towards potentially correlated groups. Nevertheless, depending on the powertrain the various objectives, y_i, could spread over a very different value range. To take into account these aspects, the Spearman's rank correlation coefficient [58], $rank_{i,k}$, between all the n_{obj} objectives and the objectives values spread are calculated and a scaling factor, s_i,

$$s_i = (\max y_i - \min y_i) \sum_{k=1,k\neq i}^{n_{obj}} 1 - rank_{i,k} \quad (5)$$

is applied when evaluating the Euclidean distance, d, for each normalized objective, x_k, as expressed in equation 6.

$$d = \sqrt{\sum_{k=1}^{n_{obj}} s_k (1 - x_k)^2} \quad (6)$$

The optimal solution is identified as the design solution with the lower Euclidean distance d.

The ICEV solution shows poor consumer, consumption and emission performances, the BEV is characterized by low range, higher cost and the lowest consumption while the HEV is generally able to reach the optimal values or at least to offer a trade-off solution between ICEV and BEV as for the emission, consumption and cost.

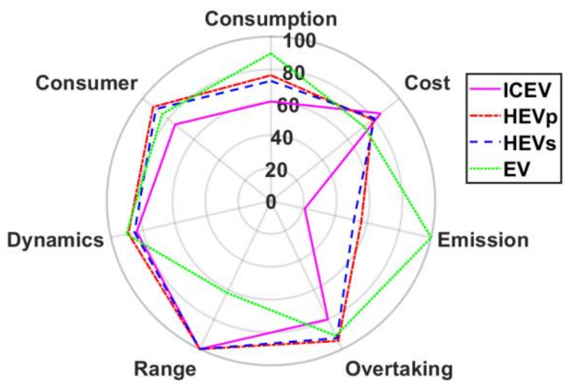

Figure 13. Spider graph of closest utopia points

Design analysis

The design analysis provides a critical overview on the main design variables for the different powertrains. Firstly, the main design variables describing the powertrain are presented. Probability distribution of values used during the optimisation are provided in Figure 14 with respect to ICE displacement, level of hybridisation (LoH), battery power rate and power split of the electric motors between rear (0%) and front (100%) axle. The battery power rate is reported with respect to nominal current rate discharge, it should be noted that the maximum discharge power reaches a value five times higher.

The ICE displacement is widely distributed over the entire range with a peak concentration in the range 1200-3000 cc. The displacement reduces moving to HEVp, 800-2400 cc, and even more in case of HEVs, 800-1400 cc. Focusing on HEV powertrains, an interesting parameter is the LoH and according to the design variables range the HEVp covers the low-medium range while the HEVs the medium-high range. Distribution's peak occurs respectively for HEVp in between 20% and 60% and for HEVs in between 40% and 90%. The battery pack sizing is quite homogeneously spread in case of BEV while HEVs and HEVp are enclosed in the region of low battery pack power of 10-20 kWh.

The power split identifies the power repartition between the front and the rear EM. The extreme values of 0 and 100% would represent respectively a rear wheel drive (RWD) and a front wheel drive (FWD) vehicle. For BEV the value ranges in between 40% and 45%, in this manner good power distribution towards optimal energy management can be achieved while dynamics is improved through an optimal traction and weight balance between the axles. This range broadens slightly in case of HEVs up to 50%, this allows to take advantage of ICE-GEN weight on the front axle to improve traction capabilities. Finally, the HEVp shows the most extreme configuration with values in between 20-30%. This occurs since on the front axle there is already the ICE providing traction and therefore it is preferable to add traction capability to the rear axle. Still a minimum value should not be exceeded in order to have enough EM power availability for the battery recharging.

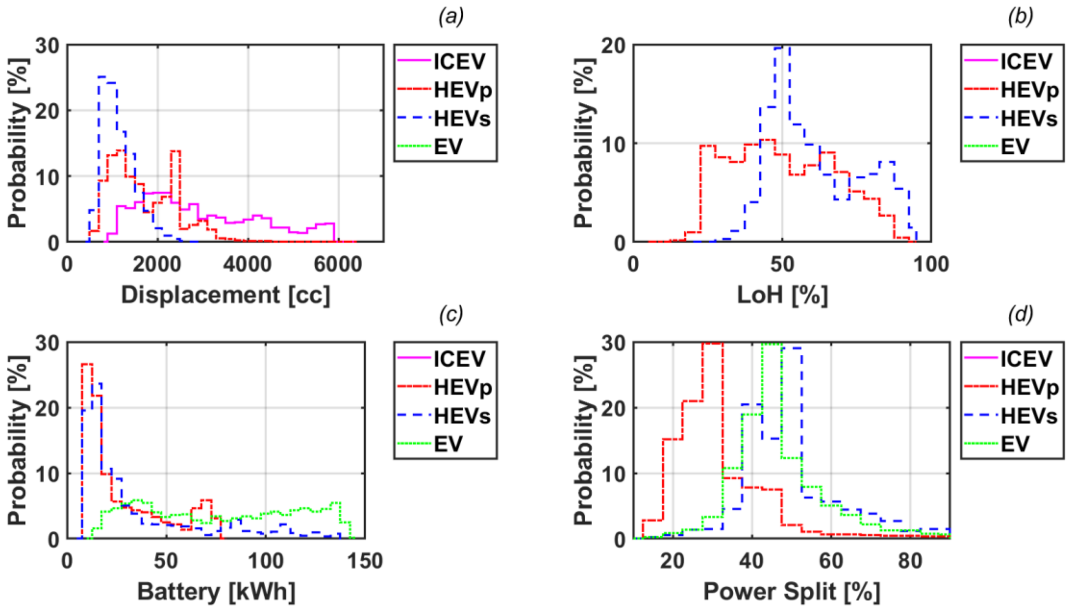

Figure 14. Main design variables probability distribution: ICE displacement (a), level of hybridisation (b), battery nominal power rate (c) and power split between electric motors (d)

In order to provide a more extensive analysis over the main design variables Figure 15 provides the maximum achievable values for consumption and dynamics accordingly to power split, level of hybridisation and vehicle maximum power. The LoH has a limited influence on consumption and dynamics with optimum solutions in the range 50-80% while the power split performs best in the range 30-60% with a deviation towards smaller values for HEVp because of the presence of the ICE set on the front axle. A very interesting trend appears when assessing the consumption dependency on the vehicle maximum power since, if in the case of ICEV and BEV an expected monotonic decreasing behaviour occurs, an almost flat shape can be observed for the hybrid architecture in a very wide range. This is due to a proper design that benefits from increasing the LoH.

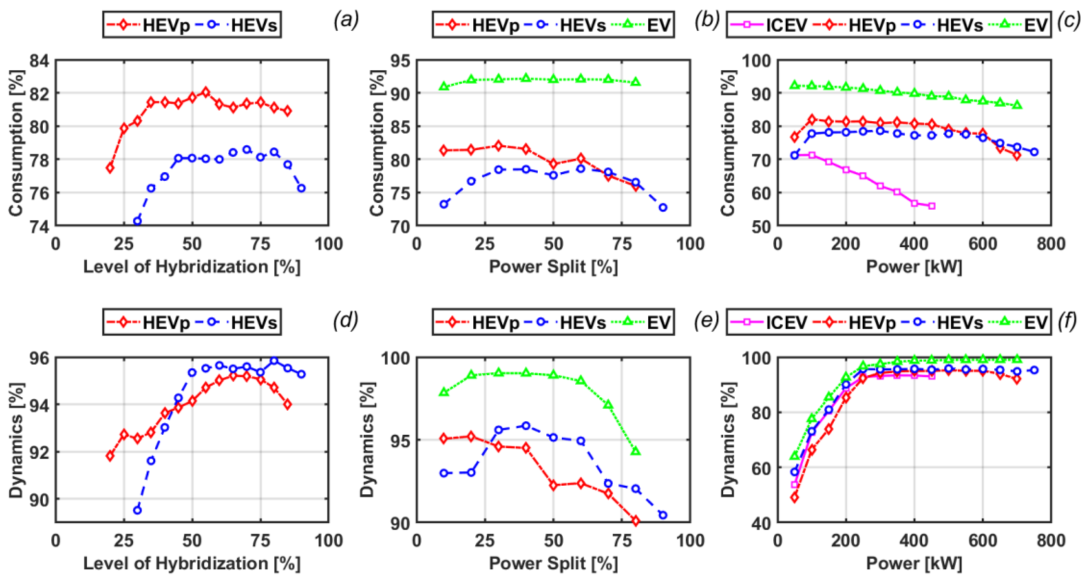

Figure 15. Level of Hybridisation, power split and vehicle maximum power influence of maximum achievable consumption (a, b, c) and dynamics (d, e, f) objectives

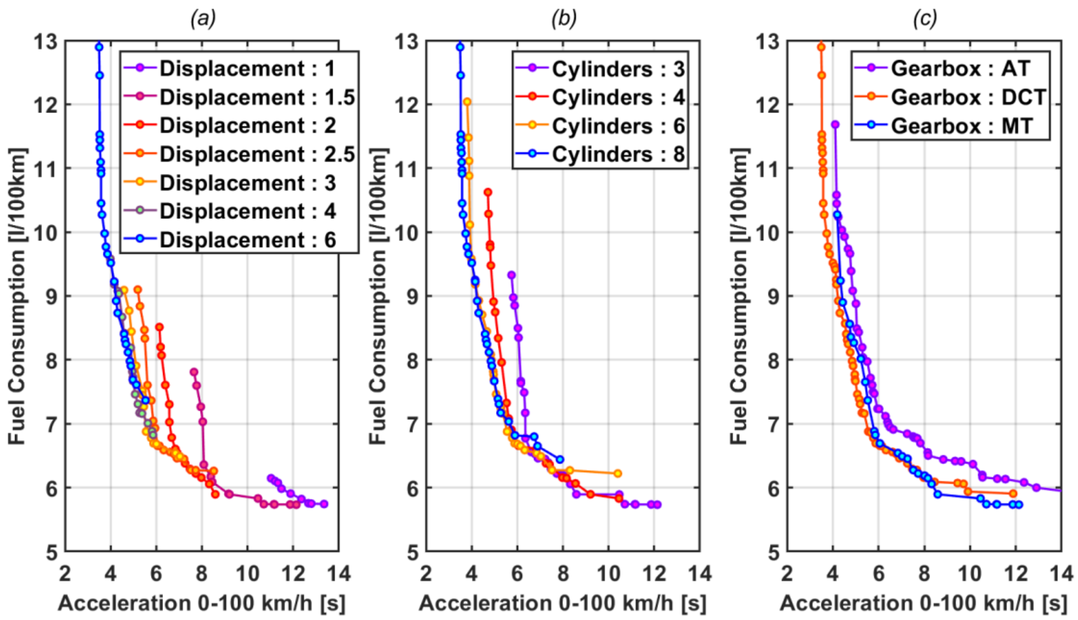

Figure 16. ICEV fuel consumption vs 0-100 km/h acceleration with respect to ICE displacement (a), number of cylinders (b) and gearbox (c)

A more detailed analysis for specific design variables is then applied considering the 0-100 km/h acceleration and respectively the fuel and the energy consumption for ICEV and BEV.
ICE displacement, number of cylinders and gearbox type are considered for the ICEV in Figure 16. Strong improvements are visible moving from 1-liter to 2-liter engines while displacement above 3 liters causes drastic increase in fuel consumption. A similar consideration occurs for the number of cylinders: 3, 4 and 6 cylinders configurations allow to cover almost the entire pareto frontier of consumption and acceleration performances while the 8 cylinder solution doesn't offer significative improvements. Finally, the three different gearbox typologies are considered showing that MT provides the most fuel

efficient solution, the DCT allows better acceleration and the AT meets the driver demand for a comfortable drive where shifting is automatically performed but consumption and acceleration are sacrificed.

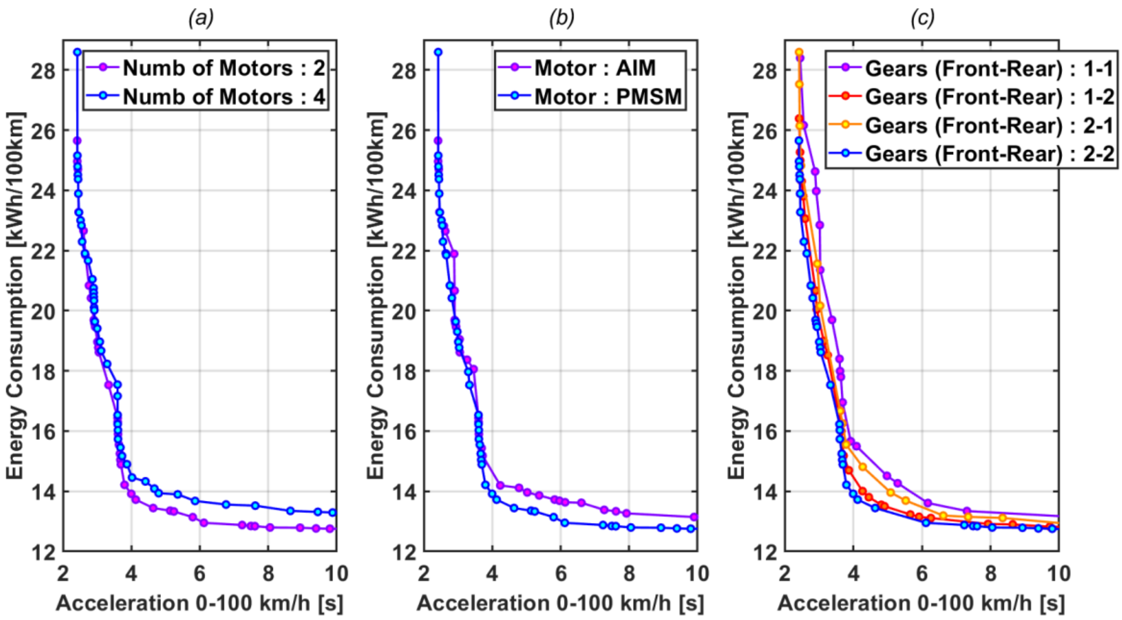

Figure 17. BEV energy consumption vs 0-100 km/h acceleration with respect to number of motors (a), motor type (b) and gearbox (c)

For the BEV the number and the type of electric motors and the gearboxes used are compared. Four electric motor configuration, hence one-motor-per-wheel, can allow to strongly improve lateral dynamics but suffer from lower energy efficiency since power distribution applies to the axles and not to the individual wheels on the same axle which would result in unacceptable driving condition on straight line. Therefore, load partition between motors on the same axle causes them to work respectively at partial loads and so at lower efficiency. The choice of the motor type is particularly relevant when energy consumption is to be minimised and therefore PMSM motors are preferred. The gearbox analysis refers to the number of gears used on the front and the rear gearbox. The simplest solution with fixed gear ratio on both axle is overcome in terms of consumption and acceleration by all the others. With a second gear on the front it is possible to improve the consumption while a second gear on the rear allows also for a better acceleration. A further improvement is provided by choosing 2-speed gearbox on both axles, but the advantage compared to the fixed-gear on the front and 2-speed on the rear are quite limited.

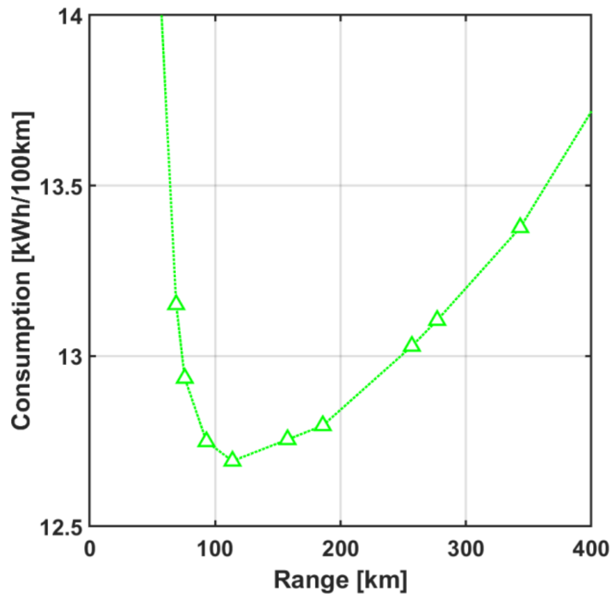

Figure 18. BEV energy consumption vs range

Another crucial aspect regarding BEV involves the range and particularly interesting is the relationship between vehicle consumption and range. For ICEV and HEV generally the range decreases with increasing consumption but by varying the fuel tank volume it is possible to have an additional design variable allowing to achieve a higher range. This is not possible for BEV for which the battery represent at the same time the power source but also the energy storage. Figure 18 provides the envelope of the minimum consumption with respect to vehicle's range and it is possible to identify a minimum consumption solution at low range. Increasing the range requires the adoption of bigger batteries which eventually affect the vehicle mass and therefore the energy consumption.

The powertrain electrification relies on electric components (motors, inverters and battery pack). The battery voltage and current identify two of the major design variables in this context. Figure 19 shows the battery maximum voltage and current for the various electrified powertrain by varying the battery nominal power.

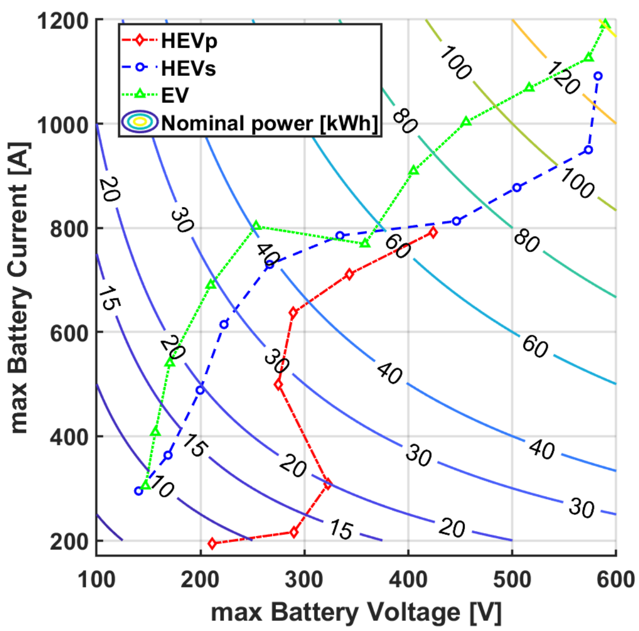

Figure 19. Battery maximum current vs maximum voltage for HEVp, HEVs and BEV according to battery nominal power levels

The simulated values are averaged over different battery nominal power levels showing that for HEVp generally a higher voltage is adopted, especially at low power rate, compared with HEVs and BEV. This is mainly due to the fact that HEVp is affected by the ICE multi-speed gearbox. The torque provided by the EM coupled with the ICE undergoes three gear stages (EM gearbox, ICE gearbox and differential) and therefore relevant buildup of the torque occurs. This results in lower torque requirements to the EM and thus of current from the battery. ICE gearbox and eventually two-speed EM gearbox allow for a very fine tuning of the EM operating conditions.

An analysis over the LoH of HEV powertrains provides further considerations regarding the selection of the battery pack and the ICE, which is limited by the condition that in both operating modes, charge depletion and charge sustain, respectively the electric traction and combustion engine have to be able to fulfill all the load conditions in the WLTP. Therefore, a minimum power for both the battery and the ICE has to be reached, this can be clearly seen in Figure 20. It shows the region covered by the simulations performed in the optimisation and a lower boundary curve can be clearly detected. This curve is compared to an analytical curve where a minimum power demand of 25 kW is set to both ICE and battery. Therefore, it is possible to notice that, to fulfill all the conditions in the WLTP, the configurations moving towards extreme values of LoH require an exponential increase in the overall vehicle power. This condition leads to expensive and high consumption vehicles. To explore the region below a workaround would be to allow the electric traction, for low LoH, and the ICE, for high LoH, to fulfill only partially the conditions faced in the WLTP. This situation could however lead to non-efficient energy management depending on the driving condition. Low electric traction would require power from the ICE but, due to partial load, the ICE would work in its low efficiency region. On the other hand, if conditions where the ICE is not able to recharge the battery are allowed, driving in such conditions could lead to a fast discharge of the battery.

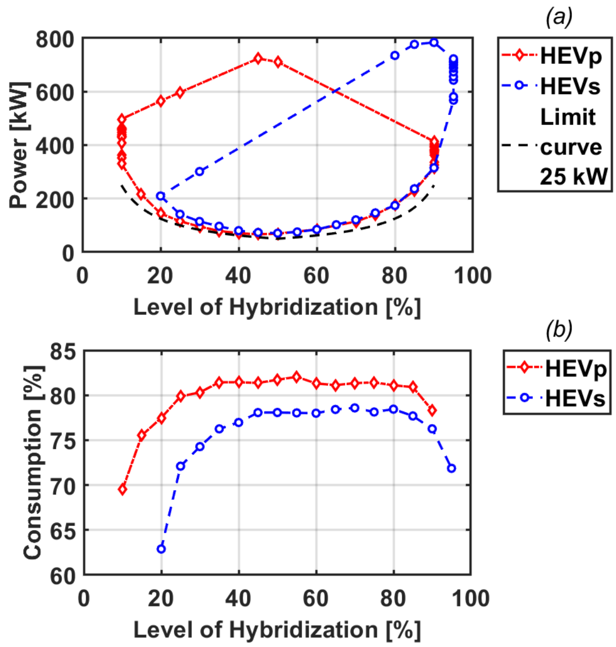

Figure 20. Region of power covered (a) and optimal consumption reachable (b) vs LoH in the optimisation for HEVp and HEVs

Considering the LoH, a further interesting aspect is the effect this design variable has on fuel consumption especially in case HEV without plug-in capabilities is deployed. This powertrain configuration relies only on charge sustaining (CS) mode during driving conditions since battery recharging is possible only through the combustion engine. This affects strongly the fuel consumption and emissions reduction because charge depleting (CD) mode, where the vehicle drives most in purely electric mode, can't be pursued.

Figure 21 shows the influence of the LoH on fuel consumption and acceleration performance accompanied with results of the minimum fuel consumption that can be obtained by varying the LoH.

Regarding the Pareto frontier of fuel consumption and acceleration performance it's possible to see that, through the optimal power management strategy adopted, the powertrain hybridisation allows to effectively reduce fuel consumption and the advantage is quite remarkable for LoH up to 60%. Further increase in LoH show only limited improvements. The results are grouped according to three levels of LoH (20-40%, 40-60% and 60-80%) and the HEVp shifts from HEVs quite similarly for all these cases. Another interesting aspect is the minimum fuel consumption by varying the LoH for vehicles with different levels of acceleration performance.

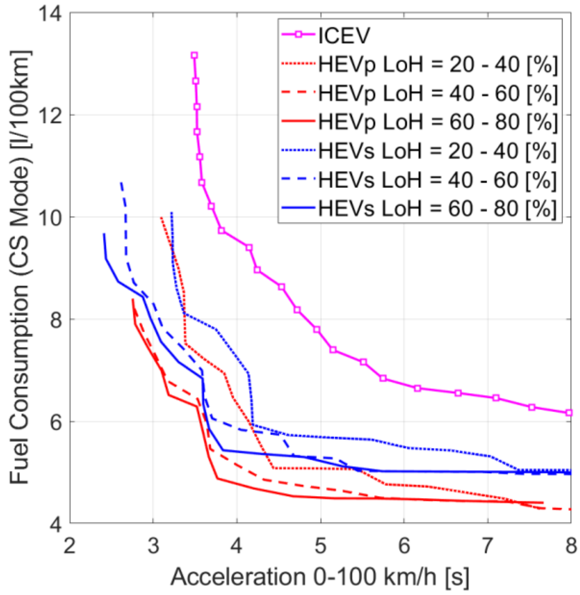

Figure 21. Influence of LoH on fuel consumption and acceleration performance in CS driving mode

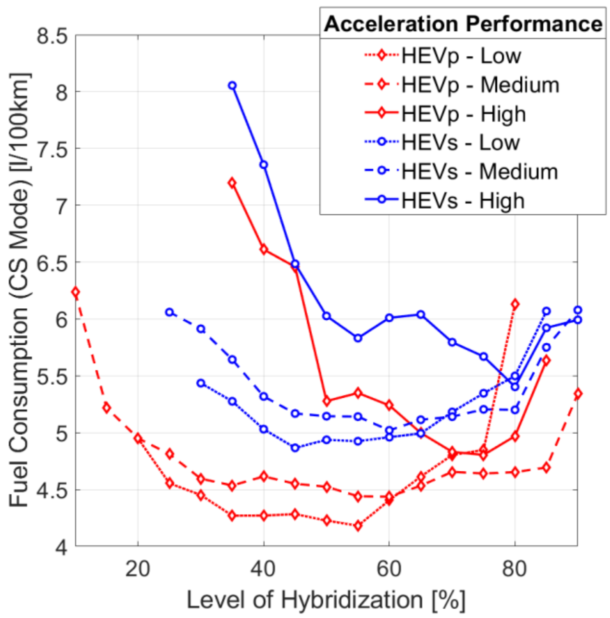

Figure 22. Fuel consumption in CS driving mode dependency on LoH

Figure 22 provides the minimum fuel consumption depending on LoH by grouping the results according to three levels of acceleration 0-100 km/h performance: low, 8-

12 s, medium, 5-7 s, and high, 2-4 s. For each level it is possible to detect an optimal LoH and nevertheless, the optimal value shifts towards higher LoH by increasing the acceleration performance level.

Conclusions

The study presented in this work provides a methodology to assess and optimize a vehicle from a conceptual design perspective. The work structure focuses on the representation of the main components of the powertrain architecture and includes the most relevant aspects from the entire vehicle. The components' definition relies on model-based approach and specifically, on scaled models allowing to estimate the component behavior on few significant design variables. The scaling procedure is driven by accurate and detailed models results and applies to internal combustion engine (ICE), electric motor (EM), inverter, battery and transmission components. The vehicle model couples the various components and specific control strategies are adopted to optimally handle gear shifting, energy management hybrid electric vehicles (HEV) and power split in configurations with multiple electric motors.

The optimization procedure considers four different powertrain architectures: conventional internal combustion engine vehicles (ICEV), hybrid electric vehicles with parallel (HEVp) and series (HEVs) configuration, and battery electric vehicles (BEV). The ICE is always considered front mounted and only all-wheel drive (AWD) systems are studied allowing for better traction behavior and, in case of multiple EM, low consumption is possible through optimal power split management. The optimization considers the major vehicle's design variables with focus on the powertrain and specific simulation are developed to the test the vehicle performance. According to the simulation results, specific objectives and constraints are defined covering consumption, emission, range, longitudinal and lateral dynamics, gradeability and costs. The definition of a specific objective, referred to as "consumer" and considering simultaneously the various objectives, provides an effective solution to speed up the optimization algorithm search towards solutions that are feasible with respect to all various objectives and nevertheless, it allows to take into account further aspects that otherwise would be difficult to properly considered.

The results allow a comparison between the different powertrain architectures. BEV represent the most promising solution towards consumption reduction or to further improve vehicle dynamics. The major issue concern the very limited range, this problem might be overcome with HEV configurations which furthermore, meet both requirements from emission regulations and from the consumer. Considering the various objectives, HEV generally represent a compromise solution between BEV and ICEV. The ICEV on the other hand, still represent the most effective solution for low cost vehicles. The results are accompanied also with an analysis over the main design variables. It is possible to see that powertrain hybridization leads to smaller combustion engines with optimal level of hybridization in the range 40-60%. Another relevant aspect is the power distribution among the electric motors on front and rear axle which strongly depends on the powertrain configurations: HEVp benefit on the front axle on ICE propulsion and therefore the electric traction is mainly distributed on the rear (80%); HEVs have a more equal distribution (50%) that allows to benefit from both rear axle traction and higher weight on front axle due to the combustion engine range extender; BEV result in a compromise solution where traction is favored by allocating more power on the rear (60%).

The study provides also consideration other various design variables as engine displacement and number of cylinders, gearbox types and number of gears, electric motor type and one-motor per wheel configuration, and battery voltage and current. The considerations are reported with respect to physical variables to better show the influence of the different design variables and energy consumption and 0-100 km/h are used for these comparisons. A final consideration over the level of hybridization used in HEV shows how this design variable affects the vehicle powertrain design and the two configurations, HEVp and HEVs are compared in terms of optimal consumption.

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Declaration of conflicting interests
The authors declared no potential conflicts of interest with respect to the research, authorship, end/or publication of this article.

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