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Article

Taxi Fleet Renewal in Cities with Improved Hybrid Powertrains: Life Cycle and Sensitivity Analysis in Lisbon Case Study

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Abstract: Stringent emissions regulations in cities and the high amount of daily miles driven by taxi vehicles enforce the need to renew these fleets with more efficient and cleaner technologies. Hybrid vehicles are potential candidates due to their enhanced powertrain, and slower battery depletion and fewer lifetime issues, relative to full electric vehicles. This paper proposes a methodology to analyze the best theoretical hybrid powertrain candidate with maximum in-use efficiency, minimum life cycle greenhouse gas emissions, and minimum additional cost, for a Lisbon taxi fleet case study. A multi-objective genetic algorithm integrated with a vehicle simulator is used to achieve several trade-off optimal solutions for different driving patterns. Potential improvements in taxi carbon footprint are discussed as a function of its lifetime, urban/extra-urban driving and maintenance/fuel life cycle uncertainty. Hybrid powertrains reveal to be advantageous comparatively to the conventional vehicle, especially in urban conditions. Specifically optimized solutions could reduce in-use energy consumption by 43%–47% in urban driving, and 27%–34% in extra-urban driving conditions, and reduce life cycle emissions by 47%–49% and 34%–36% respectively, relative to the conventional taxi. A financial gain of 50 \$/km/fleet in extra-urban and 226 \$/km/fleet in urban routes could be achieved by replacing the taxi fleet with the optimal solutions.

Keywords: life cycle analysis; hybrid powertrains; real driving; multi-objective optimization; sensitivity analysis

1. Introduction

Decision makers and governments have been introducing policies aiming to improve the efficiency of energy use, especially in the energy and transport sector, resulting from the Kyoto protocol for greenhouse gas (GHG) emissions mitigation, the 2003/30/EC European directive on biofuels for transport, and the European 20-20-20 strategy. Consequently, the automotive industry and the European Road Transport Research Advisory Council [1] have been addressing vehicle powertrain hybridization, electrification, and use of new materials, as alternative solutions to conventional road vehicles, including the use of innovative technologies and energy sources [2,3].

1.1. Road Vehicle Enhancements and Taxi Applications

In order to make the conventional internal combustion engine vehicle (ICEV) increasingly more efficient, new technological improvements are being addressed, as well as alternative fuels or fuel blends (e.g., methanol, biodiesel, natural gas, ethanol, hydrogen). Besides the implementation of start-stop systems, variable valve timing and lifting, direct injection and stratified charge engines, dual injection, turbocharging and/or supercharging, other engine options to replace the "conventional" internal combustion engine (ICE) are also being addressed: e.g., Atkinson cycle engine, Miller cycle engine, Wankel engine [4–6]. Some of these recent improvements can be already found in the latest hybrid vehicles. The gradual electrification and hybridization of the vehicle is one of the strategies adopted by both industry and the policy makers all around the developed world aiming to improve the transportation sector efficiency and reduce its associated environmental drawbacks. The implementation of new components and their proper sizing, the development of new and lighter materials, and the modification of the vehicle configuration, such as hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), pure battery electric vehicles (BEV), and fuel cell vehicles, are some of the solutions that have been researched by the automotive industry.

Among several options, the HEV still dominates the market of alternative light-duty vehicles, due to its already implemented fuel supply infrastructure, the similarity in its operation and autonomy to the conventional ICEV, and substantially relative lower cost than equivalent BEV, PHEV, and fuel cell vehicles [7]. A hybrid powertrain simply combines more than one method for the propulsion of the vehicle. Typically, one source of propulsion is provided by the conversion of a fuel into mechanical energy, and the other source is provided by using a storage component of electric energy. The regenerative braking is one of the most innovative efficiency improvements of electric and some hybrid powertrains, which can store a fraction of braking kinetic energy [6,8].

Besides several vehicle options commercially available, the HEV has been demonstrated to be advantageous in public transportation. In Sweden, which has the largest alternative taxi fleet of Europe, 19.4% of the vehicles use biogas or natural gas, 6.5% are fueled by ethanol, and 6% of all taxis are hybrids. A case study in Mexico city showed that a taxi fleet, which represents around 4% of the entire road vehicle sector and is responsible for 6% of the daily modal trips, is responsible for 13% of GHG and 10% of NO_x and CO of the road transport [9]. To address this issue, it has been proposed by the year 2028 that hybrid vehicles should replace 40% of the taxi fleet. In New York, around 60% of the taxis are hybrids aiming to reduce the pollutant emissions [10]. In London, around 1300 HEV buses are currently running in city bus routes [11], which have been claimed to reduce emissions of local pollutants and carbon dioxide by at least 30% compared to conventional diesel buses. In São Paulo (Brazil), more than 116 HEV taxis were shown to reduce the energy consumption and carbon emissions by more than 20% and 50% respectively [12].

Besides the improvements introduced by new technologies, the optimization of the vehicle powertrain should be incorporated throughout the vehicle design. The minimization of cost, life cycle emissions and energy consumption, and the improvement of the vehicle performance, are factors that cannot be neglected socially and economically, for neither the everyday user, fleet owners, nor city planners. Focusing on the powertrain sizing, many optimal design algorithms have been used to design the powertrain of different vehicle configurations, both hybrid and electric. The design variables can be the nominal power of components, number of energy storage cells, or even design characteristics of the body, transmission or final drive [13,14]. The use of a particle swarm algorithm to optimize the powertrain configuration of a plug-in hybrid electric vehicle, namely the engine power, electric motor power, and battery energy capacity, was addressed in [15], aiming to minimize the powertrain size and the fuel consumption. In this study, the decision variables were selected accordingly to the dynamic performance requirements of a specific driving cycle, which although only relied on the nominal power of the components may improve the convergence and the search domain of optimization. Besides addressing the optimization of the vehicle powertrain sizing, further research [16] has also discussed the variation of the results concerning different driving conditions. In this study a sequence of standard driving cycles, instead of a single one, was used aiming to adjust the final optimized solutions to possible driving style variations, as expected in reality. These aspects, although not regarded in this paper, should be addressed in future research.

The use of genetic algorithms applied to component optimization in alternative vehicles has been extensively considered in recent works by the author [17–20], where hybrid urban bus and taxi vehicles were optimized aiming to minimize the cost and the energy consumption of the powertrain in real and synthetic driving conditions. The simultaneous optimization of different objectives using multi-objective algorithms, aiming to minimize the fuel consumption and the GHG emissions [21], has been considered in previous studies by the author [17,22], where besides the cost and efficiency, a life cycle approach is also considered.

Although not addressed in this paper, the power-coupling component and the powertrain control strategy are fundamental aspects of hybrid powertrains, that when optimized may increase the overall efficiency of the vehicle, reduce the energy consumption or reduce the tailpipe emissions. Real-time (instantaneous) and global techniques (knowledge of the driving conditions a priori), which can be complemented with adaptive or predictive procedures, are some of the optimization methods that can be applied to hybrid control strategies. Some of these methods have already been addressed in several studies [23,24].

1.2. Environmental and Financial Burden of Alternative Vehicles

Different vehicle powertrains and characteristics result in different environmental and economic aspects. The production of the materials and energy associated to the vehicle itself and use is responsible for a specific environmental and economic impact. Therefore, the minimization life cycle impact is a factor that cannot be neglected when designing a vehicle [25]. The life cycle analysis (LCA) of a vehicle emerges as an important tool not only to evaluate the efficiency of the vehicle but also its environmental impact at a local and "global" level. The use of LCA has been used in a large number of studies to compare vehicle technologies and alternative fuels [26–29]. A review of LCA use in vehicle analysis is well expressed in [30], which highlights important aspects to take into account when structuring a LCA study. Although not all the aspects pointed out were considered in this paper, the authors believe that the suggested improvements are important for future research work.

The impact of the energy or vehicle use may be also accounted for by performing a cost analysis. This impact analysis is naturally more important to the equipment purchasers (e.g., personal vehicles, fleet owners) or to decision makers/planners. Besides performing a LCA analysis some studies conduct also a detailed review on the cost of the vehicle powertrain components [3,31,32]. In addition to the environmental and financial aspects of vehicles and fuels, several studies complemented this analysis with optimization methods aiming to mitigate the transport impact [17,18,20,22,33].

1.3. Proposed Approach

The studies mentioned above show the possibility to further improve the efficiency and the impact of hybrid vehicles through optimization of the propulsion system. However, few studies implement multi-objective optimization of the components of a full hybrid vehicle, considering the life cycle impact and the financial aspects as simultaneous optimization criteria, aiming to replace a real taxi fleet. Taxi vehicles, of which a significant share is operated by independent taxi drivers, have no predefined routes, and therefore the driving cycle is very random throughout the day [34]. Optimization studies in the context of taxi systems frequently mainly address route optimization problems e.g., [35]. A recent study evaluates alternative vehicle introduction in the taxi system but the concern is to minimize the sum of agency and user costs per trip [36]. Little work has been conducted to assess the tradeoffs between selecting various fuels/powertrains for taxis and resultant costs for taxi fleet owners as well as the associated carbon footprint impact. These aspects, besides shaping the transport sector, are becoming increasingly important nowadays, where the financial dimension severely affects the vehicle purchasers, and the environmental dimension is of great interest for policy compliance and industry planners.

This paper presents a methodology to achieve optimal trade-off solutions concerning the minimization of carbon footprint (CO_2 equivalent emissions) and, simultaneously, the taxi owner's costs, by using a life cycle approach. In order to achieve the proposed goal, a multi-objective genetic algorithm (GA) is developed. The candidate solutions are afterwards analyzed by a road vehicle simulation software and by cost and life cycle models, which together with the optimization algorithm (that arranges vehicle powertrains automatically towards the optimal solution) allow to select the best taxi configurations for Lisbon city.

Unlike most of the work that has been carried out in the same area, in addition to the powertrain sizing, different models of each component are considered (battery, engine and electrical motor). Most of the previous studies have performed only the sizing or parametrization of (fixed) components not addressing different component models with different operation maps [13,14,24]. Having different components models, and also sizing ranges, assure that a large range of torque, speed, and efficiency ranges are available (although the search process could be more computationally expensive).

One of the main advantages of the metaheuristic method used in this study is that it can be totally dissociated from the complex vehicle modelling. The freedom the GA coupled with the vehicle simulator, unconfined from any previous analytical formulation, is one of the advantages that the authors aimed to explore. In this way, some component variables that could be withdrawn by any dynamic constraint (as in [16]), may not only compose a feasible vehicle but may also achieve good efficiency or objective values when combined with other components. The complexity of the relationship between the search domain (vehicle powertrain components) and the final solutions may be attributed to the type of objective function, which unlike in this study is sometimes straightforward like minimizing fuel consumption, tail pipe emissions, and vehicle cost [13,22]. These objectives generally depend on direct calculations resultant from the optimization variables and although they may be concurrent, the objective functions are mathematically independent. In this study the objective to minimize the life cycle CO_2 equivalent emissions depends on the fuel consumption and on the vehicle materials, and the objective to maximize the financial gain depends also on the fuel consumption (fuel cost) and on the vehicle cost.

These objectives in vehicle optimization aim to produce useful insights from the perspectives of the vehicle purchaser and policy makers.

After the optimization process, a decision-making method is considered aiming to rank the obtained optimal solutions according to their overall performance in all driving events. This methodology is applicable for any vehicle technology. A current commercially available hybrid vehicle is also compared with the optimal solutions obtained from the optimization algorithm, in order to check its adequacy for taxi systems and discuss further improvements.

This work will contribute to finding more appropriate technological solutions for this sector, taking into account different driving scenarios (real and synthetic, urban/extra-urban) and different powertrain components using the Lisbon taxi fleet as a case study.

2. Taxi Vehicle Simulation

In order to evaluate the conventional and hybrid taxis, a vehicle simulation software is used, ADVISOR [37]. This software, developed by NREL, uses a combined backward-forward approach that enables the software to model vehicle powertrains, providing useful information on the vehicle performance, energy consumption, tailpipe CO_2 emissions, and components' behavior, in synthetic or real measured driving conditions. It has been demonstrated in the research community to be a reliable tool for studying energy consumption and vehicle performance and for testing energy-related control schemes [27,37–39]. Previous research [39] shows that this model has a typical 10% error for ICEV based technologies. Some of the used models were validated in previous studies [27,40], and some provided by ADVISOR [37], which have its included models validated experimentally. The simulation of the reference vehicles, as described in [41,42], present an average error less than 10%.

Despite the conventional ICEV taxi, the hybrid vehicles in this paper (both reference and the optimized solutions) are all charge sustaining hybrids, which means that only "liquid" fuel is used in the vehicle propulsion. Moreover, the battery charge sustaining is followed and no electricity is required to compensate the battery's energy depletion at the end of the vehicle trip.

2.1. Reference Taxi

Two reference taxis are used to compare the optimal solutions, a conventional diesel internal combustion engine vehicle (ICEV) and a hybrid electric vehicle (HEV). The reference ICEV is based on a real vehicle which is used in the majority of the taxi fleet in the city of Lisbon, Portugal [19,42]. The reference HEV is based on a commercially available combined hybrid vehicle developed by Toyota Motor Corporation [43], since it has been well accepted by the light-duty vehicle market being the most sold hybrid vehicle in the world [44], and being as well already used for taxi services. The specifications of the reference ICEV and HEV taxis in the city of Lisbon are presented in Table 1.

Table 1. Specifications of the HEV and ICEV taxi.

Component	Parameter	HEV [a]	ICEV [b]
Body	Curb weight (kg)/Cargo (kg)	1368/70	1405/70
	Frontal area (m^2)/Drag Coeficient	2.16/0.25	2.5/0.28
Generator	Power (kW@rpm)	44@1000–14000 rpm	-
	Max Torque (N.m@rpm)	40@1000 rpm	-
Motor	Power (kW@rpm)	60@14000 rpm	-
	Max Torque (N.m@rpm)	207@2500 rpm	-
ICE	Nominal Power (kW@rpm)	73@5200 rpm	100
	Max Torque (N.m@rpm)	142@4000 rpm	270@2000/4200 rpm
Battery	Energy capacity/Max. Power (kWh/kW)	1.3/25	-
	Initial SOC	60%	-
Accessories	Power (W)	1000	1000

[a] reference [41]; [b] reference [19].

The reference ICEV taxi is used to compare the results, and the reference HEV chassis is used to design the optimal solutions. The optimal powertrain is designed by selecting and sizing the main powertrain components (engine, electric motor, generator, battery) maintaining the rest of the vehicle equipment.

2.2. Driving Conditions

Two real driving cycles were used to simulate the taxi driving conditions, for which data were measured within the city of Lisbon area (Lisbon downtown, Baixa-Lisboa (BL) and Lisbon district, Lisboa-Cascais (LC)), by using a speed sensor, a GPS system equipped with a barometric altimeter and data recovery from the OBD (On-Board Diagnostic) vehicle interface [17] (see Figure 1). An official driving cycle was also used, the NEDC (New European Drive Cycle). In addition, the optimized results are compared in the worldwide harmonized light-duty vehicles test procedure (WLTP), which is a chassis dynamometer test cycle that is expected to replace the European NEDC procedure for approval testing of light-duty vehicles. Despite having a similar maximum VSP, the WLTP has higher average and maximum speed, and a wider range of acceleration. These small differences may cause significant variations, such as: an increase of 4 W/kg in the VSP may lead to the increase in the required power up to around 7000 W. In this way, different types of driving conditions are tested. Both synthetic driving cycles, NEDC and WLTP, are described in [45]. Table 2 presents the main characteristics of the considered driving cycles, including the vehicle specific power (VSP). VSP has been used to represent the power requested from the driving cycle to the vehicle per unit of mass (or vehicle's weight), which is estimated based upon speed, acceleration and road grade also accounting for the rolling resistance, road grade and aerodynamic drag [46].

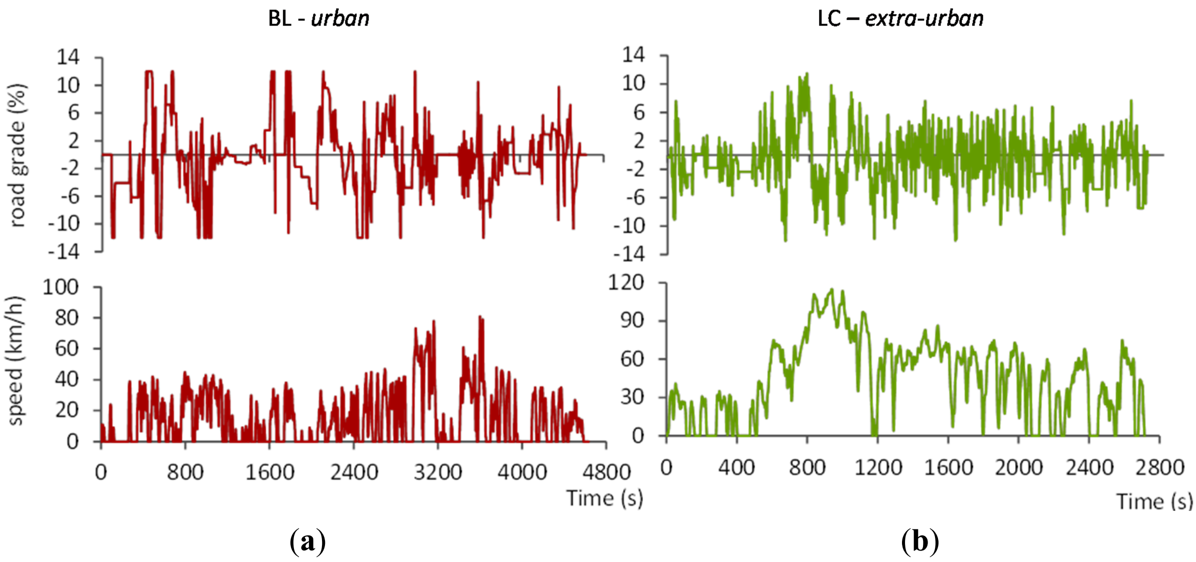


Figure 1. Road grade and speed profile of the real measured driving cycles: (**a**) BL; (**b**) LC.

Table 2. Driving cycle characteristics.

Driving cycle	Time (s)	Distance (km)	Average speed (km/h)	Max. speed (km/h)	Average accel. (m/s²)	Max. accel./decel. (m/s²)	Max. VSP (W/kg)	# Stops	Grade
NEDC (synthetic)	1184	10.9	33.2	120	0.54	1.06/−1.39	25.6	13	No
WLTP (synthetic)	1800	23.26	46.5	131	0.42	1.75/−1.48	30.1	8	No
BL (urban)	4630	20	15.5	81	0.81	4.44/−6.11	57.7	83	Yes
LC (combined, with high extra-urban share)	2705	34.2	45.5	115	0.69	3.89/−10.28	49.2	17	Yes

3. Life Cycle Environmental Analysis

The LCA methodology is used to analyze a product's flows during its entire lifetime, since it is produced, to its utilization and its end-of-life, including its recycling process.

The LCA of a vehicle usage is frequently divided in the fuel life cycle, also known as Well-to-Wheel stage (WTW), and the vehicle materials life cycle, the Cradle-to-Grave stage (CTG). The WTW aggregates the fuel consumed in the vehicle during its operation, the Tank-to-Wheel stage (TTW), and with the fuel production, distribution and storage, the Well-to-Tank stage (WTT). The vehicle materials CTG accounts for the materials production, vehicle assemblage, maintenance, dismantling and recycling. The boundaries of the LCA can be found in Figure 2. The energy used (L^E) and the CO_2 equivalent emissions (L^e) throughout the vehicle life cycle expressed per km, considering the fuel production and use, and the vehicle material stages, can be calculated by Equation (1) [17]:

$$\begin{cases} L_i^E = \{ x_k^E + y_k^E x_k^E \} + \dfrac{\sum z_{i,j}^E \; m_{i,j}}{l} \\ L_i^e = \{ x_k^e + y_k^e x_k^e \} + \dfrac{\sum z_{i,j}^e \; m_{i,j}}{l} \end{cases} \quad (1)$$

where, k is the energy source used in the vehicle, k = {diesel, gasoline}; i is the vehicle powertrain, i = {ICEV, HEV}; j is the powertrain component, j = {diesel engine, electric motor and controller, battery}; $x^E{}_k$ and $x^e{}_k$ represent the energy consumption (in MJ/km) and emissions (in g/km) from the vehicle i derived from the use of a specific fuel k; $y^E{}_k$ and $y^e{}_k$ represent the energy consumption and emissions factors (in MJ/MJ and g/MJ respectively) associated to the fuel k production in WTT stage (see Table 3); $z^E{}_{i,j}$ and $z^e{}_{i,j}$ represent the energy consumption and emissions factors (in MJ/kg and g/kg respectively) of the CTG stage considering the components j of a specific vehicle i (see Table 4); $m_{i,j}$ is the mass (in kg) of a specific component j in a specific vehicle i; l is the lifetime expected distance for the vehicle in km (Section 3.2).

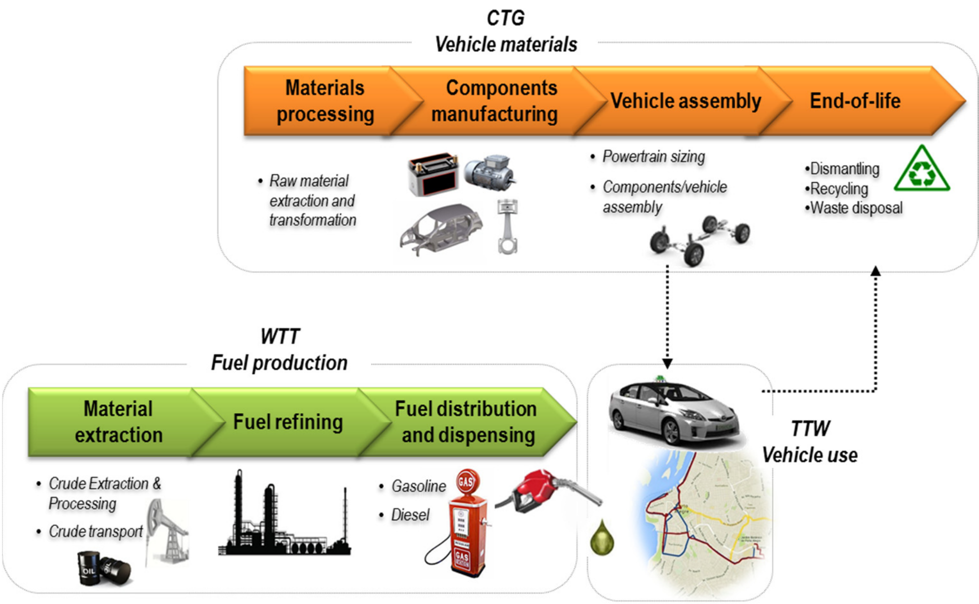


Figure 2. Life cycle stages simplified flow chart applied to a car lifetime.

Table 3. Energy and emissions WTT factor (MJ and gCO_{2eq} per MJ of final energy consumed at the vehicle) [3].

Energy k	Energy (MJ/MJ_{final}) $y^E{}_k$			CO_{2eq} (g/MJ_{final}) $y^e{}_k$		
	Average	Min	Max	Average	Min	Max
Diesel	0.16	0.14	0.18	14.2	12.6	16
Gasoline	0.14	0.12	0.17	12.5	11.1	14.6

Table 4. CTG factors (MJ and gCO_{2eq} per kg of the respective component in the vehicle) [17,47].

Component *j*	Abbreviation	Energy ($MJ/kg_{component}$) $z^{E}_{i,j}$	CO_{2eq} ($gCO_{2eq}/kg_{component}$) $z^{e}_{i,j}$
ICE system	ICE	48.13	2840
Motor & controller/generator	MC, GC	159.09	10,094
Battery (Lithium)	BAT	224.71	13,438
Battery (NiMh)		205.15	11,719

3.1. Fuel Cycle—Well-to-Wheel

In the TTW stage, the fuel consumption and the CO_2 emissions from the vehicle's tailpipe during the vehicle utilization are accounted. In this stage a clear comparison between the vehicle technologies is made, namely their efficiency and driving performance. In order to evaluate the vehicles in the TTW stage, a vehicle simulation software is used, ADVISOR [37].

The WTT stage in the life cycle refers to the extraction and production, distribution, and storage of the fuel or energy itself, and considers the energy use and CO_{2eq} emissions associated to those processes. The energy sources evaluated in the WTT stage for this study are diesel, which is used for the reference ICEV taxi, and gasoline for the HEVs.

In this study, the total energy use in the WTT pathways does not include the energy content of the produced fuel (MJ_{final}), and therefore the WTT only regards the energy used (consumed) to provide the fuel to the vehicle tank (Table 3) [3].

3.2. Materials Cycle—Cradle-to-Grave

The materials CTG accounts for the impact of the vehicle components materials during the vehicle lifetime expectancy. The European commission directive 2007/46/EC [48], indicates a distance of 200,000 km for the lifetime expectancy for a light-duty passenger vehicle. On the other hand, a study on London taxi vehicles [27] indicated a lifetime distance of 550,000 km for taxi vehicles. Additionally, a Portuguese study on taxi transportation in Lisbon city [34] revealed that a taxi vehicle travels between 54,600 km and 65,000 km per year, which considering a prescribed life period of 10 years, a taxi can travel up to 650,000 km. Therefore, in this study, three lifetime distances for the vehicles are considered: 200,000 km, 550,000 km, and 650,000 km.

The methodology and data adopted in GREET database [27,48] were used in this study. Besides ADR (assembly, disposal and recycling processes), the CTG stage of the HEV materials accounted with the impact of the following materials and consumables: vehicle fluids, tires, vehicle body and chassis, transmission, low voltage battery (lead based), high voltage battery (Li or NiMh based), ICE system, electric motor and controller, and electric generator. The vehicle body and chassis, transmission, ICE system, electric motor & controller, and generator are elements considered not to require replacement during the lifetime of the vehicle, and therefore their impact is static during the vehicle lifetime (but is dependent on the vehicle lifetime expected distance). On the other hand, the vehicle tires, batteries, and consumable fluids are expected to require replacement during the vehicle lifetime. In Table 5 the expected replacement events are presented based on the vehicle service mileage [27], accounting for the minimum and maximum distance interval travelled by the vehicle and the expected lifetime of the vehicle (minimum of 200,000 km or a maximum of 650,000 km). The CTG factors' estimation for the HEV components is described in Table 5.

Table 5. Range of the number of replacements and corresponding servicing interval in kilometers in brackets.

Components	Replacements (recommended service/km)
Pneumatics [1]	1–10 (96,560–64,373)
Engine oil [1,2]	23–133 (4828–8047)
Transmission oil [1]	1 (average)
Brakes oil [1,2]	2–25 (64,373–2 years)
Wind shield fluid [1]	14–79 (51,206–18,170)
Powertrain Coolant [1,2]	1–20 (80,467–3 years)
Lead-acid battery [3]	2 (average)
Li-ion/NiMh battery [3]	1–3 (28,1635–187,756)

[1] reference [27]; [2] reference [49,50]; [3] reference [27,51].

4. Financial Analysis

Analyzing the financial gain is extremely useful to highlight if the investment in a particular technology is advantageous. The financial gain (F_g) in Equation (2) accounts for the added cost of the HEV powertrain and its fuel costs (gasoline) over its estimated lifetime, relative to the conventional vehicle (ICEV taxi). Positive values ($/km) represent "virtual" money saved per km, implying that it may be worthwhile to invest in such alternative powertrains.

$$F_g = (-1)\left\{ \left(\frac{C_i}{l} + p_i\, x_k^E \right)_{\substack{i=alternative \\ HEV}} - \left(\frac{C_r}{l} + p_{diesel}\, x_{diesel}^E \right)_{\substack{reference \\ vehicle}} \right\} \quad (2)$$

where, Alternative vehicle refers to the optimized alternative vehicles i in this paper; C_i is the powertrain cost of vehicle i, determined by the sum of the components costs c_j in Equation (3), C_r is the powertrain cost of the reference ICEV vehicle; l is the travelled distance considering the life time expected in kilometers; p_k is the cost (in dollars, $) of the fuel k per MJ consumed in the vehicle I; $x^E{}_k$ is the fuel consumption at the vehicle.

In this study, Portuguese average costs (for the user) were assumed for diesel and gasoline: 0.0647 $/MJ$_{gasoline}$ (1.534€/liter$_{gasoline}$) for gasoline and 0.0512 $/MJ$_{diesel}$ (1.375 €/liter$_{diesel}$) for diesel [52]. Note that the energy costs are far from being stationary.

The cost for each component was estimated to attribute a "virtual" cost to each vehicle powertrain, in order to compare the powertrain investment of the different vehicles (see Equation (3)). The estimated costs c_j in Equation (3) for each component j, are estimated based on several cost analysis studies which assume large volume production scale [17,31].

$$c_j = \begin{cases} c_{ICE} = 30P + 2200 \\ c_{GC} = P\,(20\,(P/m_{MC}) + 0.25) \\ c_{MC} = P\,(20\,(P/m_{MC}) + 0.25) \\ c_{BAT\,Li} = E\,(368\,|ln(P/E)| + 177) \\ c_{BAT\,Ni} = 0.8\,E\,(368\,|ln(P/E)| + 177) \end{cases} \quad (3)$$

where, Li stands for Lithium and Ni stands for Nickel-metal hydride; P is the nominal power (kW); m is the mass of the component; E is the energy capacity of the battery (kWh).

5. Optimization of the Hybrid Powertrain

5.1. Problem Formulation

The goal is to seek the best powertrain for a HEV configuration to equip a real taxi, aiming to maximize the financial gain and minimize the life cycle CO_{2eq} emissions, relative to a conventional diesel taxi (see Equation (4)). The resultant optimal vehicle must comply with several constraints: (i) maximum speed higher than 120 km/h, (ii) acceleration from 0–100 km/h must be performed in less than 15 s, and, (iii) battery state-of-charge variation ($\Delta SOC = SOC_{initial} - SOC_{final}$) should be less than 2% (SAE regulations for charge sustaining [53]).

The maximum speed and the acceleration constraints are evaluated directly by the vehicle simulator for each assembled vehicle. The ΔSOC variation is also reported by the vehicle simulator, however a *SOC Correction* procedure must be considered in order to guarantee that the charge sustaining operation of the battery is maintained throughout the driving cycle (ΔSOC < 2%). The SOC correction routine adjusts the initial SOC or the general energy control until the simulation run yields a zero change in SOC plus a specified tolerance band. The routine will run for a maximum number of iterations until it converges (usually less than 10 iterations). The detailed algorithmic process is included in ADVISOR documentation [37,53]. Note that the SOC Correction may attribute increased fuel consumption to a specific vehicle simulation in order to compensate the battery charge depletion at the end of a driving cycle (or reduced fuel consumption if at the end of the cycle the ΔSOC is positive).

The objective function can be defined as in Equation (4):

$$\begin{cases} max\ f_1(\alpha) = F_g(\alpha) \\ min\ f_2(\alpha) = L^e(\alpha) \end{cases} \tag{4}$$

where, f_1 (α) is the financial balance (as in Equation (2)); f_2 (α) is the life cycle CO_{2eq} emissions (as in Equation (3)); α_i represents the optimization variable vector (see Table 6).

Table 6. Optimization variables for each vehicle powertrain configuration: components design and EMS.

Optimization variables	Variables values range
ICE_{model}	{1, 2, 3, 4}
ICE_{size}	[0.5, 2]
GC_{model}	{1}
GC_{size}	[0.5, 2]
MC_{model}	{1, 2, 3, 4}
MC_{size}	[0.5, 2]
BAT_{model}	{1, 2, 3, 4}
$BAT_{modules}$	[5, 100]

The components constituting the vehicle powertrain are the optimization variables. The characteristics of the original components (as the optimization variables) are presented in Tables 6 and 7. Four different gasoline fueled ICE models, four MC models, one GC model, and four BAT models, are available to select from for the design of the optimal vehicle powertrains. Each MC can achieve an overtorque ([8]) operation for a limited time, having its torque multiplied by 1.8 (overtorque factor).

Besides the selection of the component, a sizing routine is used to size each component based on its nominal characteristics. The component is sized accordingly to a scale parameter, in which the value of 1 regards to the original component, 0.5 to the component sized to half of its nominal power, 2 to match the double of its nominal power, and so on [20,22].

Table 7. Powertrain components models.

Components	Components models			
ICE model	ICE_1 [a]	ICE_2 [b]	ICE_3 [c]	ICE_4 [d]
Power (kW)	43	73	66	50
Weight (kg)	137	173	158	130
MC model	MC_1 [e]	MC_2 [f]	MC_3 [g]	MC_4 [h]
Power (kW)	64	18	104	76
Weight (kg)	57	57	102	57
GC model	GC_1 [i]			
Power (kW)	38			
Weight (kg)	33			
BAT model	BAT_1 [j]	BAT_2 [k]	BAT_3 [l]	BAT_4 [m]
Min./Max. voltage (V)	2.5/4.1	2.7/4.2	6/9	10.25/14
Capacity (Ah)	7	40	5.5	34
Weight (kg)	0.35	1	1.04	9
Type	Cell	Cell	Module	Module
Chemistry	Li-ion	Li-ion	NiMh	NiMh

[a,d,f,l] ADVISOR; [b,i] reference [41]; [c] reference [40]; [e,g,h,j,k,m] reference [17].

The range of the optimization variables α, *i.e.*, components models and their sizing range, was selected so that the possible powertrain solutions have the capacity, power and performance, which cover a wide range of requirements of the driving conditions to the resultant light-duty vehicle, or taxi in this case. The sizing range for each component ensures that low power and high power powertrains are incorporated in the possible solutions. The knowledge of the potential powertrain requirements has been acquired from previous studies [22,42], the driving cycle power requirements (see Table 2), and from commercially available hybrid vehicles (e.g., Toyota Prius, GM Volt, and Honda Insight).

5.2. Multi-Objective Optimization Algorithm

A non-dominated sorting genetic algorithm (NSGA-II) is used for the multi-objective optimization [17,54]. The genetic algorithm seems particularly suited for the considered optimization problem, and it is a very robust algorithm to solve nonlinear, nonconvex, and discrete problems, alike to the vehicle optimization problem in this study. Moreover, this method can be coupled with a vehicle simulation software and automatically evaluate the vehicle performance being dissociated from the complex modeling of the system, focusing only on the solutions' convergence.

The selection of the components and the sizing factors (as in Tables 6 and 7) are generated by the genetic algorithm. The variables α represent genes in the genetic chromosome of the NSGA-II, which characterize a vehicle or an individual, and a possible solution. Figure 3 shows a scheme of the used genetic algorithm and its integration with the methods used to evaluate the solutions.

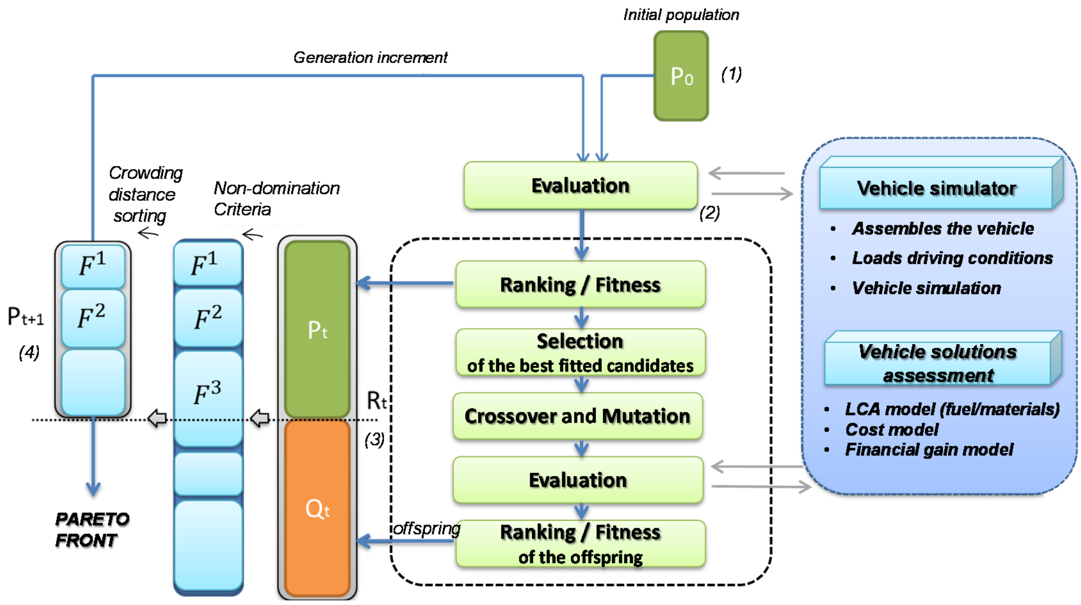


Figure 3. Implementation of the NSGA-II including its integration with ADVISOR platform, LCA calculations and cost calculations.

The optimization process has the following steps:

(1) Initially, a random parent population of size n individuals, is created, P_0.

(2) The population is evaluated and sorted based on the non-domination concept.

The evaluation procedure consists in the simulation of each individual from the population P, in ADVISOR, followed by the LCA and financial assessments (see Sections 3 and 4). These results are used to assess the optimization objective and the non-domination evaluation. Each individual (candidate solution) is assigned a fitness (or rank) equal to its non-domination level (1 is the best level, 2 is the next-best level, and so on). At this point the parent population P is ranked (P_t). An offspring population, Q_t, is created from the best ranked individuals from P_t, which are selected accordingly to a binary tournament operator, recombined (intermediate crossover) and mutated, in order to form new individuals (offspring).

(3) A combined population R_t with the size of $2n$ is formed: $R_t = P_t \cup Q_t$.

The population R_t is sorted accordingly to its non-domination ranking, and grouped in sets. Solutions grouped in the set F^1 belong to the best (ranked) non-dominated set, which have the best chance to be selected to form the new population P_{t+1}. The following non-dominated sets F^2, F^3 have a lower ranking and therefore lower chance to be selected to form P_{t+1}.

The non-dominating sorting procedure aims to distinguish the solutions' closeness to the *Pareto* front. Consider a population of individuals, or candidate solutions, $P = [\alpha_1\ \alpha_2\ \ldots\ \alpha_n, \alpha_m]$, and a certain number of objectives, θ. A decision vector α_n dominates a decision vector α_m, if and only if: α_n is not worse than α_m in all objectives, *i.e.*, $f_\theta(\alpha_n) \leq f_\theta(\alpha_m)$, $\forall_\theta$; and α_n is strictly better than α_m in at least one objective, *i.e.*, $\exists_\theta$: $f_\theta(\alpha_n) < f_\theta(\alpha_m)$. A solution α_n is a non-dominated solution if there isn't any other solution that dominates α_n, in the terms defined above. A crowding distance sorting is applied to the individuals before forming the new population P_{t+1}. The crowding distance sorting aims to maintain the diversity of solutions based on the density of solutions in the space [54].

(4) A generation is complete, and now the new population P_{t+1} become a parent population and the process is repeated. The final non-dominated set, the *Pareto* front, is achieved if one of the stopping criteria is reached: maximum number of generations (200), or if an average change in the spread of the *Pareto* front over a specified number of generations (150) is less than a specified tolerance (0.001).

5.3. Multi Criteria Score Approach

An alternative and simple decision making approach is proposed, where a score is attributed to each optimal solution in the *Pareto* front. The scores take into account the following criteria μ: cost, fuel consumption (TTW), LCA $CO_{2eq.}$ emissions and financial gain (Sections 3 and 4). In this way, new and possible interesting decision criteria are also evaluated besides the optimization objectives. All the relevant vehicle solutions are considered, as well as the driving cycles.

First, the obtained optimal vehicles (and the reference HEV) are sorted according to their performance relative to each criterion μ. Points (p_μ) are assigned to each sorted position. The best vehicle in criteria μ (with less cost, fuel consumption, LCA impact, or maximum financial gain) receives the highest amount of points (6 points) and is classified as #1. The second best receives 5 points, and so on. Finally, the points assigned to each vehicle relative to each criteria achievement are converted into a score value (see (7)), for each vehicle and driving cycle (or total). The solution with the highest score is the preferred solution by this method.

$$Score^{vehicle} = \sum_{\substack{driving\\cycle}} W_{\substack{driving\\cycle}} \left(\sum_{criteria\ \mu} (W_\mu\, p_\mu) \right) \tag{5}$$

where, $W_{driving\ cycle}$ is a weighting factor for each driving cycle assumed to be 1 (equal weight for each cycle); W_μ is a weighting factor for each criteria μ (in this study all criteria are assumed to have the same influence $W_\mu = 1$); α_i represents the optimization variable vector (see Table 6).

Although in this study equal weighting factors (W_μ, $W_{driving\ cycle}$) are assumed to each criteria and driving cycle, they can be adjusted to different case studies. The weights attributed to each criterion vary according to the decision maker's particular value system and should be interpreted as measures of the degree to which each criterion influences a final statement of whether or not an alternative is preferred over another. Note that cost and fuel consumption are indirectly accounted for in LCA impact and financial gain objectives.

6. Results and Discussion

The sets of optimal solutions for the HEV taxi are presented in Figure 4 to Figure 6 for the respective driving cycle and different lifetimes. One of the characteristic outcomes of the used multi-objective algorithm is a set of optimal solutions (Pareto set), which especially occurs in optimizing conflicting objectives: vehicle solutions A1 and A2 were optimized for NEDC driving cycle (Figure 4), vehicles B1, B2 and B3 correspond to the ones optimized for BL driving cycle (Figure 5) and vehicles C1 and C2 correspond to the vehicles optimized for LC driving cycle (Figure 6). Table 8 summarizes the main characteristics of the optimized vehicles.

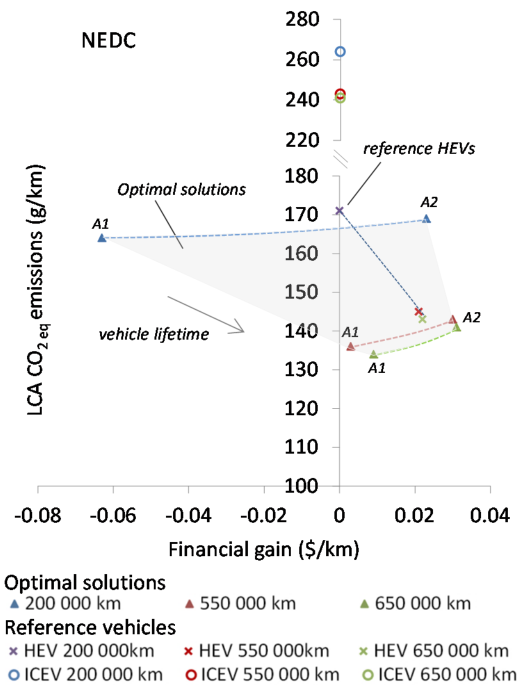


Figure 4. Set of Pareto solutions for multi-objective optimized HEVs concerning NEDC and several life time distances, and comparison with the reference vehicles (ICEV and HEV).

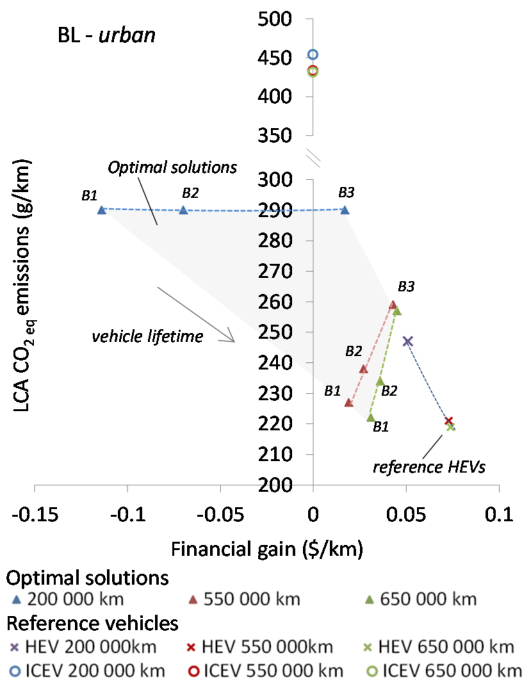


Figure 5. Set of Pareto solutions for multi-objective optimized HEVs concerning BL cycle and several life time distances, and comparison with the reference vehicles (ICEV and HEV).

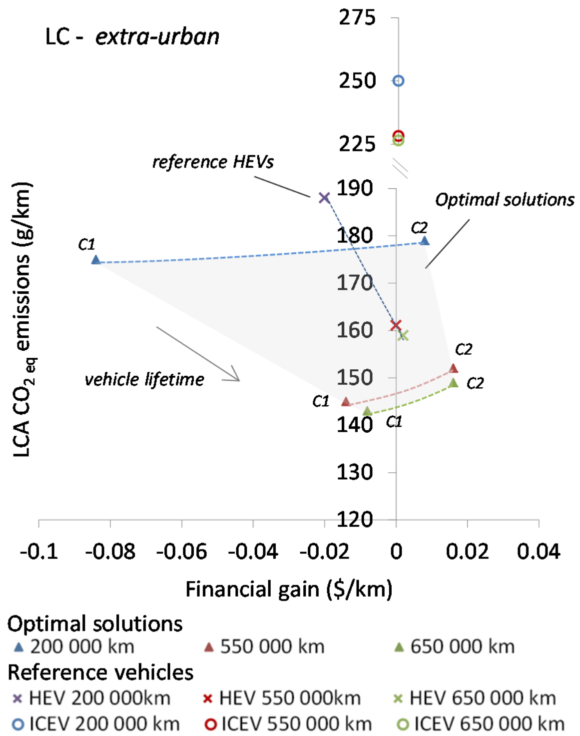


Figure 6. Set of Pareto solutions for multi-objective optimized HEVs concerning LC cycle and several life time distances, and comparison with the reference vehicles (ICEV and HEV).

Table 8. Main characteristics of the optimized taxi.

		ICE			MC			GC		BAT				Vehicle mass
		Model *	Size *	(kW)	Model *	Size *	(kW)	Size *	(kW)	Model *	Modules *	(kW)	(kWh)	(kg)
NEDC	A1	2	0.70	51	1	0.96	61	0.58	22	2 (Li-ion)	69	145	9.9	1408
	A2	2	0.69	50	1	0.72	46	0.51	19	3 (NiMh)	59	56	2.5	1384
BL	B1	2	0.89	64	3	0.75	78	0.74	28	4 (NiMh)	59	310	24.5	1924
	B2	2	1.09	79	1	1.51	96	0.81	30	4 (NiMh)	42	221	17.5	1813
	B3	2	1.48	107	1	1.75	112	1.18	44	3 (NiMh)	78	74	3.3	1601
LC	C1	2	0.73	54	1	1.08	69	1.36	51	2 (Li-ion)	70	148	10.1	1449
	C2	2	0.79	57	3	0.55	57	1.32	50	3 (NiMh)	47	44	1.9	1427

* model and size as in Table 7.

All the different solutions presented for each driving cycle (e.g., A1 and A2) achieved optimality conditions, characterized by a trade-off between the objectives, and therefore, the smaller the impact of the life cycle is, the less financial return obtained. In some cases, the lowest life cycle impact implies no financial return (C1 solutions in Figure 6). Tables 9 and 10 present the solutions objective values achieved in detail. Since the domain containing feasible solutions is very specific and narrow (the set of available components must be arranged to compose a compatible powertrain for the vehicle), and due to the mandatory constraints with which the vehicles must comply, the Pareto set of solutions is composed by a few solutions only.

It is interesting to note that the reference vehicle HEV is not achieved by the NSGA-II algorithm but should be, in fact, an optimal for the BL driving cycle. The engine operation and general control strategy were not optimized in this paper, which is recommended in future research, and this could potentially improve energy consumption and the emissions results obtained. In addition, the reference vehicle could be benefiting from an improved control strategy that was not optimized for any of the solutions. It is also fair to consider the possibility that the obtained solution is still a local minimum despite strong attempts to overcome this issue. The genetic algorithm itself could need some improvements in order to achieve a higher number of possible solutions closer to the Pareto front (where the reference vehicle may be encountered). The enhancement of the search domain, covering more powertrain components that are feasible but more adapted to the problem scope, and improvement of the trade-off between the initial population (reference vehicle) and the diversity operator, are some aspects that could be improved in future research. This may improve the quality of the solutions as well as the optimization convergence.

As it can be seen from Table 8, solutions A1, B1, B2, C1 show a battery pack with a higher power rating than that of the combined motor and generator output. However, if considering the overtorque factor that the electric motor can allow (by a factor of 1.8), only solutions A1, B1, B2 are shown to have an oversized battery. In terms of sizing, the goal would be to get all of the potential of all components, and thus, the battery should have sufficient power to supply to the GC-MC set, but should not be too oversized. Oversized components may spend more resources than needed and increase the vehicle weight and cost [8]. Despite all this, these solutions were selected as the ones that minimized the optimization objectives.

The independence of the GA coupled with the vehicle simulator that provides the vehicle powertrain arrangement and solution search, unconfined from any previous analytic formulation, is one of the advantages that the authors aimed to explore. In this way, some component variables that could be withdrawn by any previously defined dynamic constraint (as in [16]), may not only compose a feasible vehicle but may also achieve improved efficiency values when combined with other components. This may occur since the objectives are not straightforward, and they depend on the cost, efficiency, and total life cycle of each component and assembled vehicle, besides having to comply with certain performance requirements. In some cases, the selection of an oversized component may also result in higher efficiencies. For instance, the engine could be sized such as its nominal power curve is slightly above the estimated driving requirements. In this way the engine will operate more frequently on the highest efficiency range as possible. On the other hand, a larger electric motor could also be used in hybrid powertrains to cover low efficiency operation zones of the engine. (Chapters 7 and 9 in [8]). Naturally, these aspects highly depend on the control strategy implemented in the powertrain, which although not addressed in this paper deserves a detailed analysis and optimization study.

Note that the best efficiency zones of each engine have different ranges, especially in the torque variable, as it can be seen in Figures A1–A5 (Appendix A). For instance, comparatively to the solutions B1 and B2, the vehicle B3 operates the least in the highest efficiency range of the engine, which could justify the lowest overall efficiency demonstrated by the highest fuel consumption (Table 9). For each Pareto set of optimized solutions (A, B and C) it is clear the different use of each component. This may justify the different "zones" of the Pareto solutions. An optimized control strategy could be useful in selecting the best operation schemes for each engine, concerning also the use of the battery power, in order to improve the vehicle efficiency.

Table 9. Life cycle energy use and CO_{2eq} emissions regarding the optimal solutions and the reference powertrains, for the different driving cycles (NEDC, BL, LC) and lifetime distances.

Driving cycle	Vehicle	Life cycle energy use (L^E) and CO_{2eq} emissions (L^e)																	
		200,000 $km_{lifetime}$						550,000 $km_{lifetime}$						650,000 $km_{lifetime}$					
		L^E (MJ/km)			L^e (g/km)			L^E (MJ/km)			L^e (g/km)			L^E (MJ/km)			L^e (g/km)		
		av.	min	max	av.	min	max	av.	min	max	av.	min	max	av.	min	max	av.	min	max
NEDC	A1	2.23	2.04	2.45	164	153	182	1.86	1.72	2.02	136	127	147	1.83	1.69	1.99	134	125	145
	A2	2.31	2.12	2.52	169	158	186	1.96	1.81	2.12	143	134	154	1.93	1.79	2.09	141	132	152
	HEV	2.31	2.11	2.53	171	157	187	1.97	1.82	2.14	145	134	157	1.95	1.80	2.11	143	132	155
	ICEV	3.44	3.24	3.64	264	248	282	3.18	2.98	3.38	243	226	260	3.15	2.95	3.35	241	224	258
BL	B1	4.28	3.51	5.08	290	249	341	3.23	2.84	3.64	227	206	253	3.14	2.78	3.52	222	202	246
	B2	4.18	3.57	4.82	290	257	334	3.34	3.00	3.71	238	219	262	3.27	2.95	3.61	234	216	256
	B3	4.00	3.69	4.34	290	273	319	3.56	3.31	3.84	259	245	279	3.52	3.28	3.80	257	242	276
	HEV	3.36	3.09	3.65	247	229	269	3.02	2.81	3.26	221	205	239	3.00	2.78	3.23	219	203	237
	ICEV	5.93	5.58	6.29	454	425	486	5.67	5.32	6.02	433	404	464	5.65	5.30	6.00	431	402	462
LC	C1	2.38	2.18	2.61	175	163	193	1.99	1.84	2.16	145	136	157	1.96	1.81	2.12	143	134	155
	C2	2.44	2.25	2.64	179	168	196	2.08	1.93	2.25	152	143	163	2.05	1.90	2.21	149	141	161
	HEV	2.54	2.32	2.77	188	173	204	2.20	2.04	2.39	161	149	175	2.18	2.01	2.35	159	147	172
	ICEV	3.25	3.06	3.45	250	234	267	2.99	2.81	3.18	228	213	245	2.97	2.78	3.15	226	211	243

Figures 4–6 show that there are optimal solutions for a HEV taxi, with higher financial return and less impact on the life cycle than a conventional ICEV taxi. However, regarding the reference HEV, the alternative optimal solutions are only advantageous in the NEDC and LC driving conditions, meaning that for the BL driving cycle the reference vehicle is already the best solution.

Comparatively to the ICEV taxi, the optimal HEV A1, reference HEV, and optimal HEV C1 (regarding respectively to the NEDC, BL, and LC driving cycles), could potentially reduce 35%–42%, 43%–47%, and 27%–34% of the life cycle energy use, and reduce 42%–44%, 47%–49%, and 34%–36% of the CO_{2eq} emissions (Table 9). The fuel consumption reflects the SOC correction at the end of the driving cycle.

Table 10. Powertrain cost ($) and financial gain ($/km) regarding the optimal solutions and the reference powertrains, for the different driving cycles (NEDC, BL, LC) and lifetime distances.

Driving cycle	Vehicle	Powertrain cost	Financial gain (F_g) ($/$km_{lifetime}$)		
		($)	200,000 $km_{lifetime}$	550,000 $km_{lifetime}$	650,000 $km_{lifetime}$
NEDC	A1	27,804	−0.063	0.003	0.009
	A2	9506	0.023	0.030	0.031
	HEV	13,793	0	0.021	0.022
	ICEV	7072	-	-	-
BL	B1	49,031	−0.114	0.019	0.031
	B2	37,541	−0.070	0.027	0.036
	B3	14,964	0.017	0.043	0.045
	HEV	13,793	0.051	0.073	0.074
	ICEV	7072	-	-	-
LC	C1	29,100	−0.084	−0.014	−0.008
	C2	9501	0.008	0.016	0.016
	HEV	13,793	−0.02	0	0.002
	ICEV	7072	-	-	-

Concerning the financial aspect, the optimal HEV A2, reference HEV, and optimal HEV C2 achieved the highest financial gains, for the respective driving cycles independent of the lifetime distance (Table 10). Note that the maximization of the financial gain and the minimization of the life cycle impact result in different solutions (concurrent optimization objectives). Nevertheless it is clear that the lifetime of the vehicle has a beneficial influence on the financial gain and on the emissions' reduction overall, especially due to the investment cost dilution and the cumulative lower fuel consumption over the entire vehicle use.

The BL driving cycle represents the most urban driving conditions considered, followed by the LC and the NEDC, which are mostly combined cycles. The BL driving cycle is related to higher energy consumption and higher emissions, at a local level and at a global level (as shown in the LCA analysis in Figures 7–10, and Table 9). Usually (as shown for fuel cell vehicles in previous studies by the author [17]), in urban characteristics as in this driving cycle, since more power is required to fulfill the urban driving characteristics (Table 2), more powerful components are also needed to equip the vehicles, as shown in Table 8. In these conditions, the electric propulsion may be an advantage in terms of efficiency due to the higher efficiency of the electric motor and battery compared to the fuel engine in stop-start events. Nevertheless, large powertrain electrification only becomes advantageous if the increase of the vehicle weight (by using a larger battery pack) is surpassed by the gain in the powertrain efficiency. In the BL cycle, representative of the most urban driving conditions, the weight increase really is substantial in those driving characteristics with significant road grades, becoming a drawback instead of an advantage concerning the fuel consumption. Therefore, the selection of solutions with minimum LCA impact or maximum financial gain accounts these aspects (Figure 7). Note that in order to determine the power of components, it only takes one event of high power to limit the minimum power required to the powertrain, and not the average characteristics. In order to better understand the driving cycle differences, plots of the engine, motor and battery use of the optimized solutions for BL and LC driving cycles are shown in Appendix A.

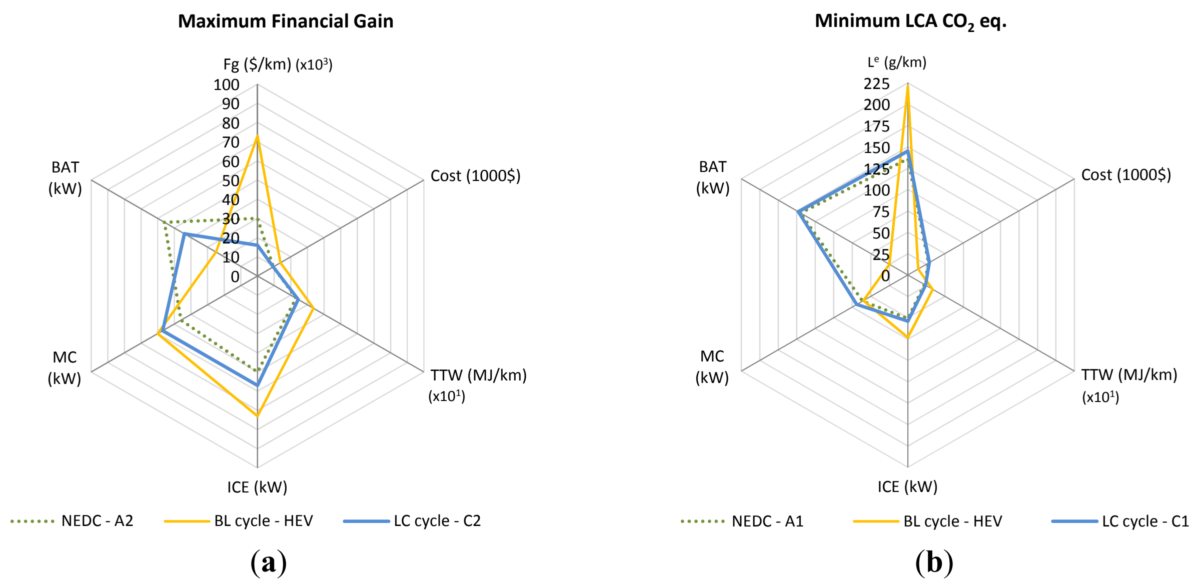
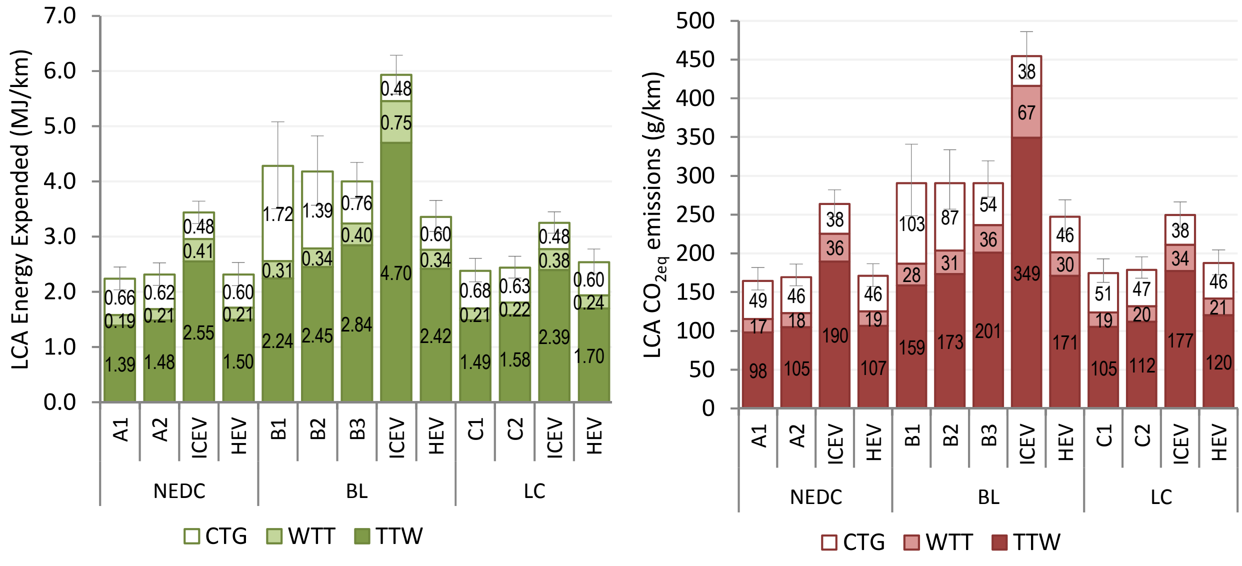


Figure 7. Main components nominal power, vehicle cost, and fuel consumption, of for the "best" vehicles for each driving cycle (NEDC, BL-urban, LC extra-urban) concerning (**a**) maximum financial gain and (**b**) minimum LCA CO_{2eq} emissions.

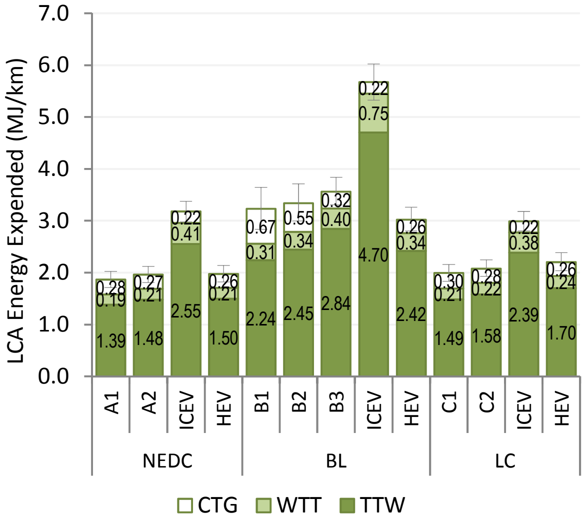
As shown in Table 8, there is a large range of possible powertrain components, and it is interesting to note that for each driving cycle there are two distinct options for the battery: one of higher power and higher capacity, and other of lower power and lower capacity. The implemented methodology aims to define the best powertrain components concerning all the available options, despite some of the options that are more frequently seen in plug-in hybrids (higher capacity batteries). In fact, the battery size is a significant aspect in the trade-off of the optimization objectives, influencing the cost, life cycle, and also the efficiency. The use of a large battery can also be explored by analyzing different energy management strategies, which may be addressed in future works.

Concerning the battery chemistry, although both Lithium and Nickel based batteries can achieve similar power and energy requirements, their energy/power density are slightly different which can lead to different vehicle weights and fuel consumption results consequently. Nevertheless, if on the one hand the energy/power density preferences the selection of the lithium based chemistry, the cost benefits the selection of the Nickel based battery. Although the algorithm and additional constraints may be improved in future work to better define the components and avoid oversizing, this aspect is crucial in the conflict between the objectives creating an added difficulty in the process convergence.

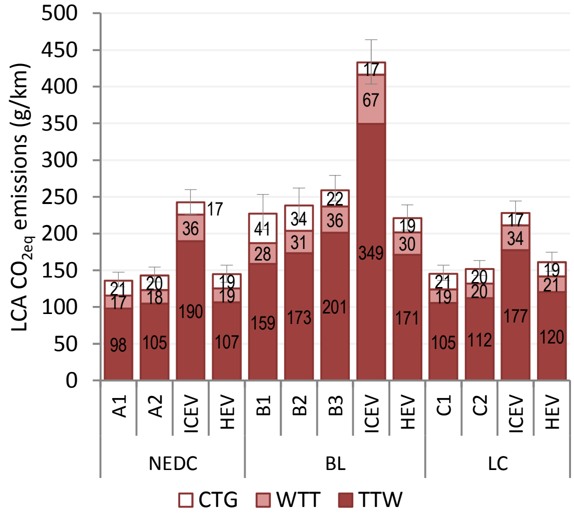


(a) **(b)**

Figure 8. Life cycle energy use (**a**) and CO_{2eq} emissions (**b**), of the reference and optimal vehicles in NEDC, BL and LC driving cycles, for a lifetime distance of 200,000 km.

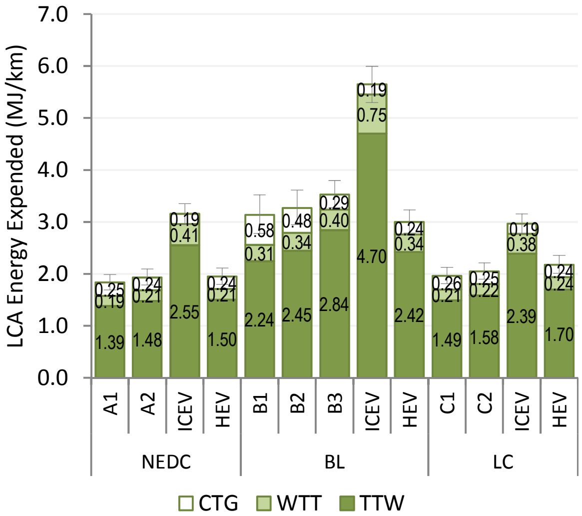


(**a**)

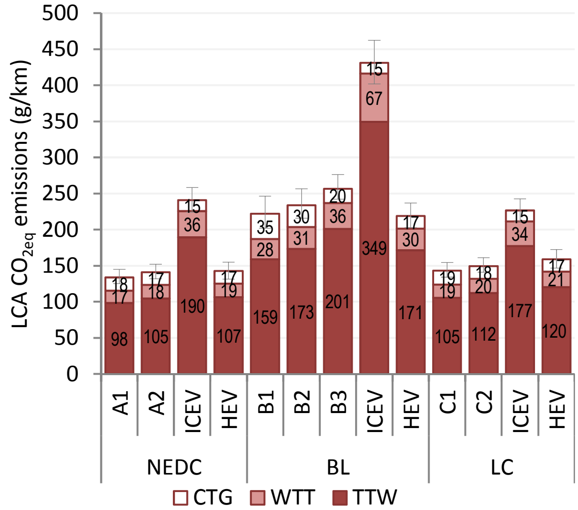


(**b**)

Figure 9. Life cycle energy use (**a**) and CO_{2eq} emissions (**b**), of the reference and optimal vehicles in NEDC, BL and LC driving cycles, for a lifetime distance of 550,000 km.



(**a**)



(**b**)

Figure 10. Life cycle energy use (**a**) and CO_{2eq} emissions (**b**), of the reference and optimal vehicles in NEDC, BL and LC driving cycles, for a lifetime distance of 650,000 km.

The maximization of the financial gain is associated with vehicles with the best balance between the investment cost of the powertrain and its efficiency. Aiming to achieve higher financial gain, the powertrain electrification, which is used to decrease the fuel consumption, is selected more carefully, in order not to significantly increase the vehicle cost (and therefore the battery pack does not increase as in the LCA minimization as shown in Figure 7). Maximizing financial gain has two important approaches, vehicle cost and efficiency.

On the other hand, the LCA depends mainly on the TTW stage, the fuel consumption, as shown in Figures 8–10. As opposed to full electric and fuel cell technologies [17], the TTW stage has the highest impact on the life cycle of internal combustion engine powered vehicles (ICEV or hybrids), regarding the energy use and emissions, meaning that the efficiency of the vehicle has a major impact on the life cycle of this kind of vehicles. Besides that the considered vehicles are hybrids, the gasoline engine is still a relative drawback in terms of fuel efficiency and emissions. The WTT stage is very dependent on the fuel use (TTW), and therefore, any improvement in the fuel use will have an impact on those stages. In this way, to achieve lower LCA impact the vehicle has the tendency to rely on larger powertrain electrification, with larger batteries, in order to achieve higher efficiencies (relatively the use of the internal combustion use) (see also Figure 7). The battery allows to better control the power flow between the components, and to better control the use of the engine in a more efficient mode [40,55]. Nevertheless, this may cause the CTG stage of the life cycle to increase. The minimum the life cycle impact is achieved by solutions A1, B1 (and reference HEV in this driving cycle), and C1, which are associated with powertrains more dependent on more powerful batteries (highest CTG stages but lowest LCA). In general, the fuel production stage, WTT, has a balanced share comparatively to the vehicle materials stage, CTG (Figures 8–10).

Concerning the life cycle of hybrid and conventional vehicles, the hybridization of the powertrains clearly improves the fuel efficiency at the vehicle, and consequently leads to lower TTW and WTT impact. Nevertheless, the battery pack that is used in the hybridization of the powertrain is responsible for the increase of the CTG stage and cost of the vehicle. The battery pack, depending on its size (Table 8), can be responsible for 30%–70% of the CTG and 44%–83% of the cost of the powertrain.

The battery, besides having a major environmental and financial impact, is claimed to require replacement during the vehicle lifetime. This ambiguity as well as the fuel price to the consumer imputes some variability to the obtained results. Figures 11–13 show the estimation of the financial gain variation regarding the effect of the battery replacement times, and the fuel price variation, for different lifetime distances of the vehicle. The vehicles used in this analysis were the optimal solutions with the highest financial gain (A2, B3, and C2, as in Table 10). It was also assumed that the diesel price (conventional ICEV taxi) and the gasoline price vary to the same extent.

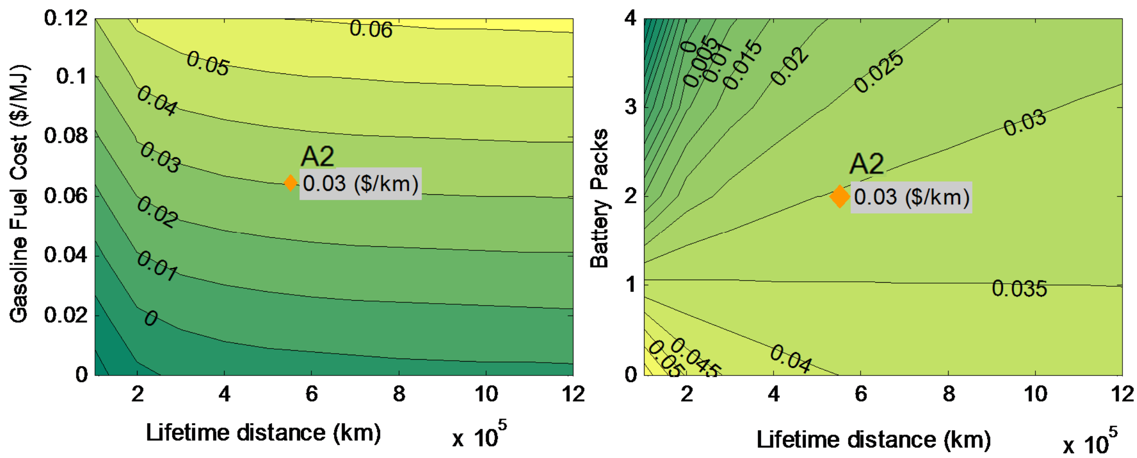


Figure 11. Financial gain considering the gasoline cost and the number of battery packs for the NEDC driving cycle, of optimal solution A2.

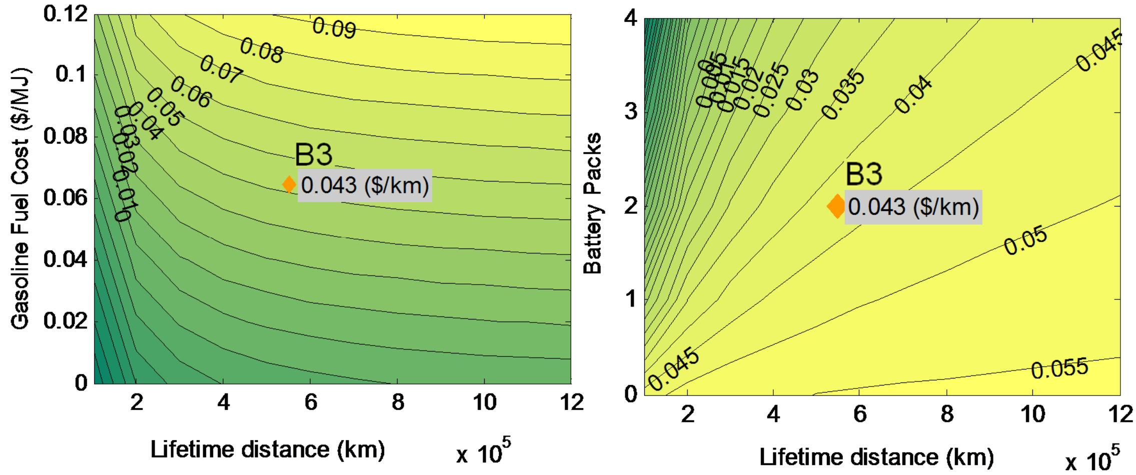


Figure 12. Financial gain considering the gasoline cost and the number of battery packs for the BL driving cycle, of optimal solution B3.

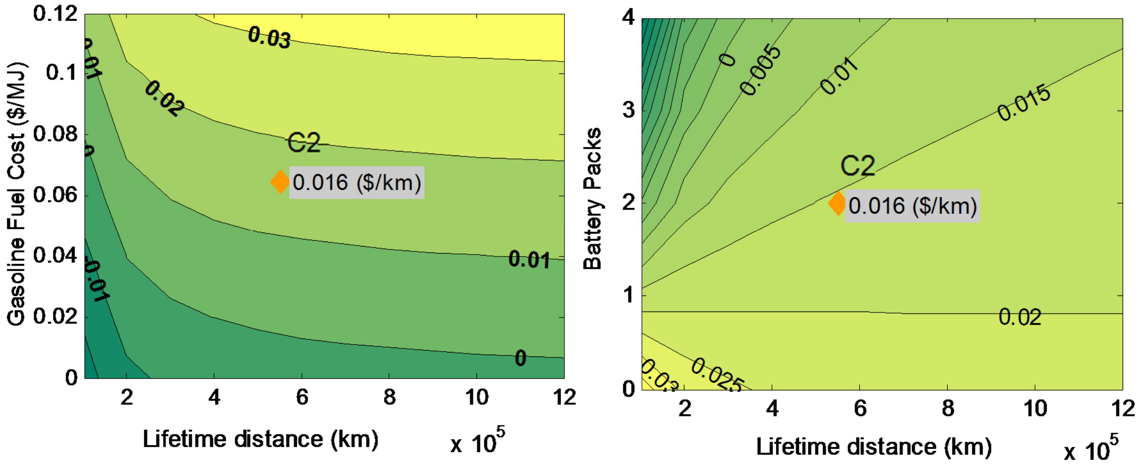
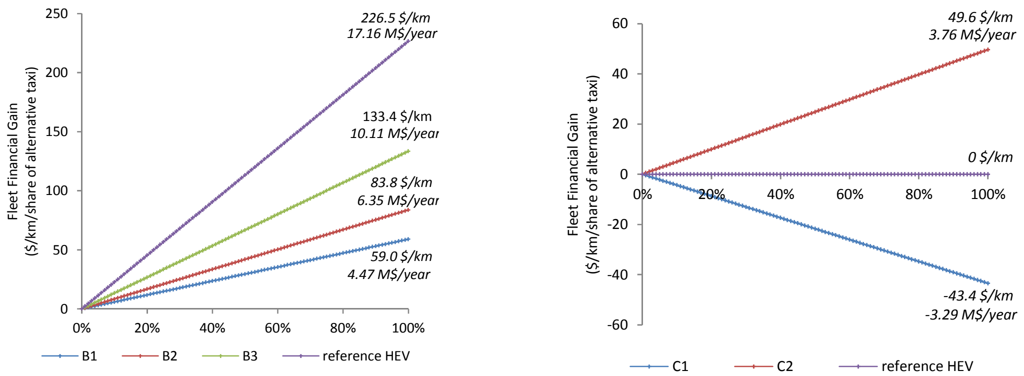


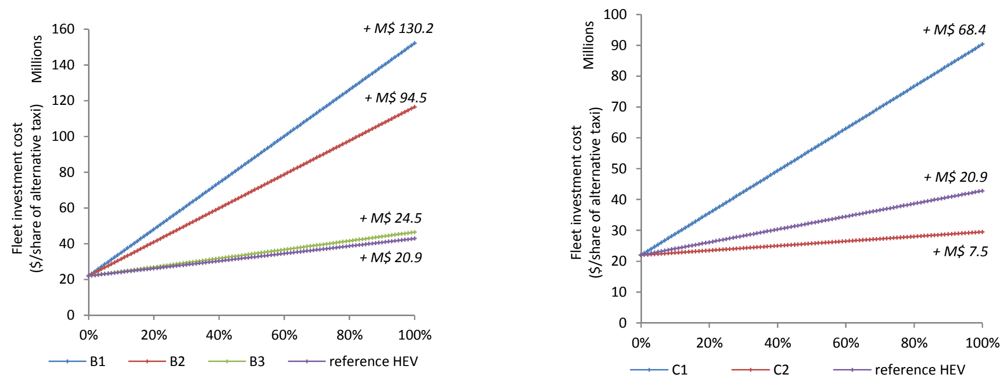
Figure 13. Financial gain considering the gasoline cost and the number of battery packs for the BL driving cycle, of optimal solution C2.

If accounting for the total number of licensed taxis circulating daily in the city of Lisbon, 3103 in the year 2013 [34], 226 $/km could potentially be saved for the entire licensed fleet for urban driving conditions (BL driving cycle), meaning around 17 million dollars of annual savings (considering that the annual fleet covered a distance of 75,743 km/taxi [56]) (Figures 14–16). Additionally, this option could also potentiate the reduction of almost 50 thousand Tons of GHG emissions from the taxi fleet (Figure 16), and a reduction of 41.8 thousand tons of local air pollutants in the city downtown. This scenario is the most significant since the average taxi service distance is 5–15 km [56], which means that the majority of the driving conditions should be purely urban. Nevertheless, if extra-urban driving is assumed, the use of the optimal HEV taxi for the entire fleet could allow saving up to 3.76 million dollars annually and reducing by 18 thousand tons the GHG emissions. This analysis however does not account for maintenance costs and taxes.



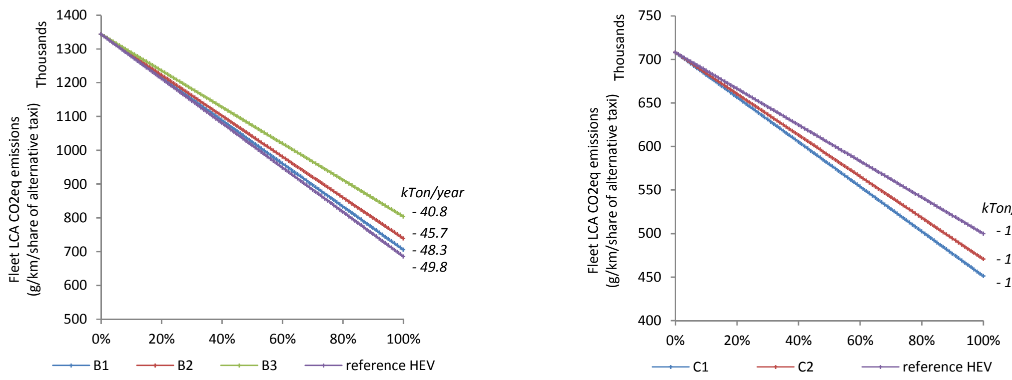
(**a**) (**b**)

Figure 14. Taxi fleet financial gain for a scenario of 0 to 100% of conventional taxis replaced with the optimized solutions, or reference HEV, for BL (**a**) and LC (**b**) driving cycles.



(**a**) (**b**)

Figure 15. Taxi fleet investment cost for a scenario of 0 to 100% of conventional taxis replaced with the optimized solutions, or reference HEV, for BL (**a**) and LC (**b**) driving cycles.



(**a**) (**b**)

Figure 16. Taxi fleet LCA CO_{2eq} emissions for a scenario of 0 to 100% of conventional taxis replaced with the optimized solutions, or reference HEV, for BL (**a**) and LC (**b**) driving cycles.

The discussion on the optimized solutions for each driving cycle aimed to highlight the maximum potential of replacing the conventional taxi vehicles with optimal hybrid solutions. To ensure the feasibility of this scenario, it should include a customized design for a vehicle for each specific driving cycle. However, this simply is impractical. However, it is possible to obtain an estimate of the optimal vehicle for a specific range of different driving conditions. In this way, the optimized solutions for the real driving cycles were simulated in different cycles in order to compare the performance variations and their impact on the optimization objectives. Besides the real driving cycles, the WLTP (world light-duty harmonized test procedure) was introduced to compare the results. The BL optimized vehicles were simulated in the LC and in the WLTP driving cycles; and the LC optimized vehicles were simulated in the BL and in the WLTP driving cycles. In addition, a decision method, the multiple criteria score approach (Section 5.3), was implemented aiming to select one unique solution. Table 11 and Table 12 show the obtained results, as well as the final vehicle ranking based on the scores attributed to the solutions. In Appendix A, the engine, motor and battery use for the optimized vehicles, simulated in the real cycles, are shown in order to compare the different powertrains.

Table 11. Fuel consumption (TTW), LCA CO_{2eq} emissions, and financial gain of the reference vehicles (ICEV and HEV) and optimal solutions for BL, LC and WLTP driving cycles. (bold values indicate a solution optimized for that specific cycle).

	BL			LC			WLTP		
	TTW (MJ/km)	**L^e (g/km)**	**Fg ($/km)**	**TTW (MJ/km)**	**L^e (g/km)**	**Fg ($/km)**	**TTW (MJ/km)**	**L^e (g/km)**	**Fg ($/km)**
ICEV	4.70	433	-	2.39	228	-	2.37	227	-
HEV	2.42	221	0.073	1.70	161	0	1.59	155	0.002
B1	2.24	227	0.019	1.97	190	−0.082	2.23	205	−0.099
B2	2.45	238	0.027	2.19	201	−0.075	2.15	193	−0.073
B3	2.84	259	0.044	2.48	214	−0.052	2.41	201	−0.049
C1	1.73	150	0.089	1.49	145	−0.014	1.52	134	−0.017
C2	2.20	188	0.094	1.58	152	0.016	1.58	137	0.016

Table 12. Ranking of "best" solutions and total score attributed to the reference vehicles (ICEV and HEV) and optimal solutions for BL, LC and WLTP driving cycles, concerning the score approach.

Vehicle	Veh. cost	Total of points (BL, LC and WLTP)				Ranking
		TTW	**L^e**	**Fg**	**Total score**	
HEV	5 (#2)	14 (#3)	15 (#3)	17 (#2)	42	#3
B1	1 (#6)	12 (#4)	10 (#4)	2 (#6)	18	#4
B2	2 (#5)	10 (#5)	10 (#4)	3 (#5)	18	#5
B3	4 (#4)	6 (#6)	7 (#6)	4 (#4)	14	#6
C1	3 (#3)	21 (#1)	21 (#1)	6 (#3)	44	#2
C2	6 (#1)	18 (#2)	18 (#2)	21 (#1)	54	#1

Concerning the financial gain, the optimal vehicle C2 (original optimized in LC cycle) achieved the highest values in all of the three driving conditions simulated, BL, LC and WLTP. In relation to the life cycle impact, the optimal vehicle C1, followed by C2, achieved the lowest CO_{2eq} emissions in all cycles. The same vehicles also achieved the lowest fuel consumption in all driving cycles (TTW stage).

It can be seen in Appendix A, that the C1 and C2 solutions achieved a large amount of points of operation between the bet efficiency range of the selected engine (similarly to B1 and B2 solutions, although these vehicles weighted more and therefore consumed more fuel that C1 and C2). Although the cost of the vehicle may have a significant influence, this may also be balanced by the financial gain. Comparatively to the reference HEV these solutions achieved a downsized engine but an upsized electric drive.

Overall, for driving conditions within the range of the ones simulated, the vehicle C2 (57 kW ICE, 50 kW generator, 57 kW motor, and a 44 kW NiMh battery pack with 1.9 kWh) was the optimal powertrain which managed to achieve the best results, followed by the vehicle C1 (54 kW ICE, 51 kW generator, 69 kW motor, and a 148 kW NiMh battery pack with 10 kWh).

7. Conclusions

Applying multi-objective optimization with real driving cycles allowed to obtain a portfolio of optimal HEV alternatives to the conventional in-use ICEV taxi. Although HEVs were the subject of the case study, the methodology can be extrapolated to study plug-ins, BEVs or conventional engine based vehicles. The optimization process, the NSGA-II coupled with the vehicle simulator, revealed the need for further improvements to achieve a higher number of optimal solutions, such as: the enhancement of the search domain, and covering more components that are feasible but more adapted to the problem scope, such as implementing inter-component constraints (avoiding undesirable solutions, exaggerated oversizing, and delaying convergence). In order to improve the battery sizing process, the configuration of the battery pack (series/parallel module arrangement) aiming to better determine the power, energy capacity and voltage output, should also be included as a constraint in future works.

The driving conditions were shown to have major impact on the optimized components (battery, electrical motor, internal combustion engine) of the taxi powertrains. Urban driving conditions require more powerful components, especially the battery and electric motor. However increasing the vehicle weight may have a drawback effect on the efficiency, which creates a conflict between the objectives of reducing the emissions and achieving higher financial savings. Nevertheless, all the hybrid solutions achieved greater efficiency compared to the ICEV, in both urban and extra-urban conditions.

The use of real driving cycles instead of the standard NEDC highlighted the need for using specific driving cycles in the simulations of real case studies, or a carefully selected driving profile adapted to the vehicle purpose. The score method considered for the decision-making process can help select one optimal solution taking into account additional criteria besides the optimization objectives. This method although applicable to other case studies, highly depends on the weightings attributed to the considered driving cycles and criteria. Based on the results the optimal configuration for the Lisbon taxi fleet for a combined urban-extra-urban use is a HEV powertrain 57 kW ICE, 50 kW generator, 57 kW motor, and a 44 kW NiMh battery pack with 1.9 kWh). Overall, this solution, besides being financially advantageous to the reference hybrid (which is financially and environmentally advantageous *per se* comparative to the conventional ICEV taxi) has also up to 9% lower fuel consumption and 15% less life cycle emissions for all the simulated driving conditions. It is noteworthy that the obtained solution is similar to the reference HEV. However, it is also worth noting that small enhancements in the powertrain can also yield improved results in other driving conditions. The engine operation and general control strategy were not optimized in this paper; however, this could potentially improve energy consumption and emissions. Nonetheless, replacing 10% with the taxi fleet for the best alternative solutions for each driving cycle could potentially save 1.7 million $/year for urban routes and 0.37 million $/year for extra-urban routes. Replacing the entire fleet permits a fossil fuel reduction of 34%–47%, and a reduction of 36%–49% of the carbon footprint for extra-urban and urban routes respectively, besides lowering the urban emissions. The higher the taxi lifetime, the higher the number of component replacements (especially battery and tires) needed, however, the financial gain increases due to the investment costs being averaged out over the total kilometers traveled by the vehicle. Therefore, hybrid powertrains may be advisable for city taxi fleets, and policies should enforce such technologies, accounting also for the possibility to implement specific powertrains according to the taxi driving area.

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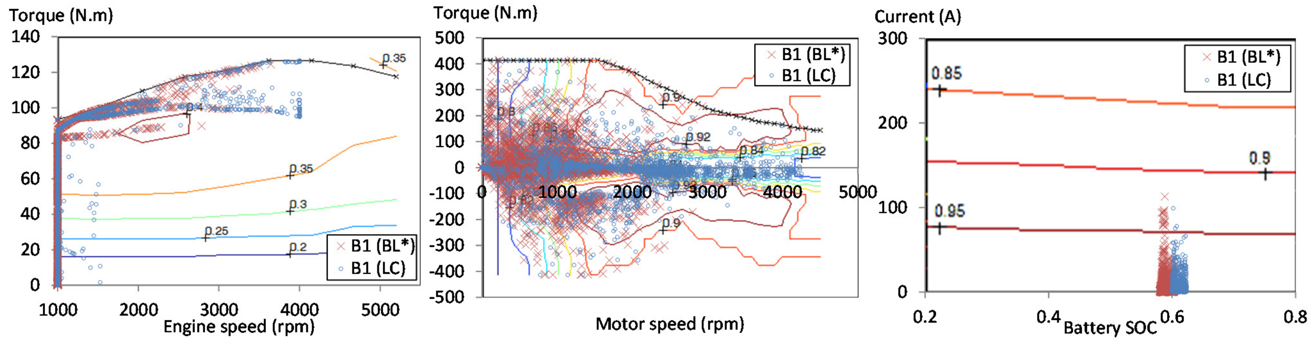
Author Contributions

António P. Castel-Branco and João P. Ribau developed the algorithm to perform the vehicle optimization. João P. Ribau and Carla M. Silva analyzed the data and wrote the paper.

Conflicts of Interest

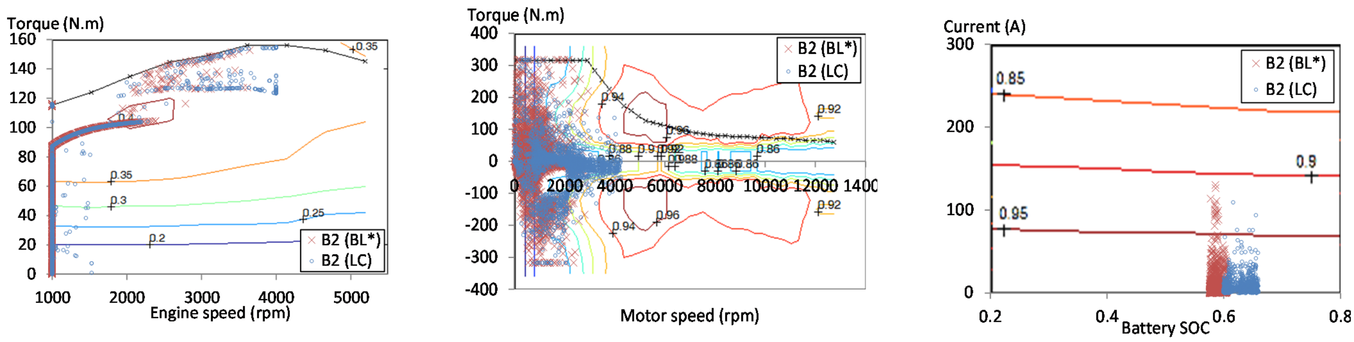
The authors declare no conflict of interest.

Appendix A



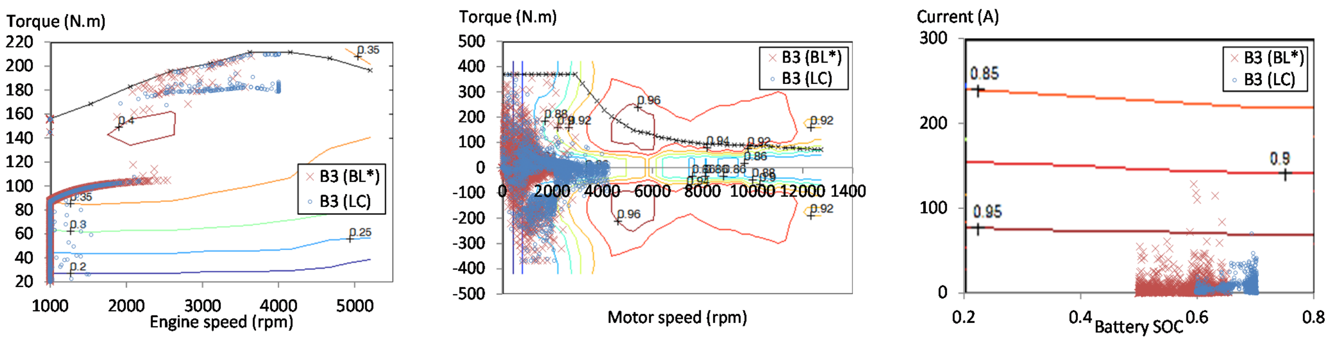
(**a**) (**b**) (**c**)

Figure A1. Plots of B1 solution engine (**a**), electric motor (**b**), and battery (**c**) operation for BL and LC driving cycles. (* driving cycle used in the optimization).



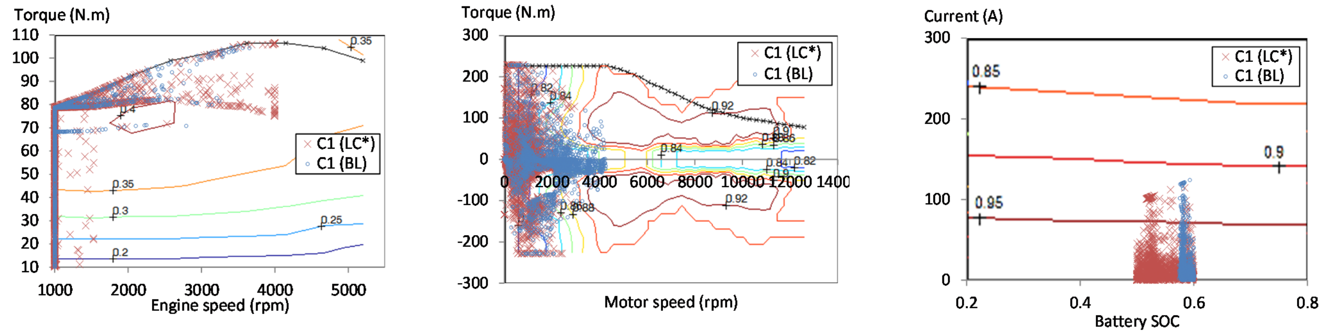
(**a**) (**b**) (**c**)

Figure A2. Plots of B2 solution engine (**a**), electric motor (**b**), and battery (**c**) operation for BL and LC driving cycles. (* driving cycle used in the optimization).



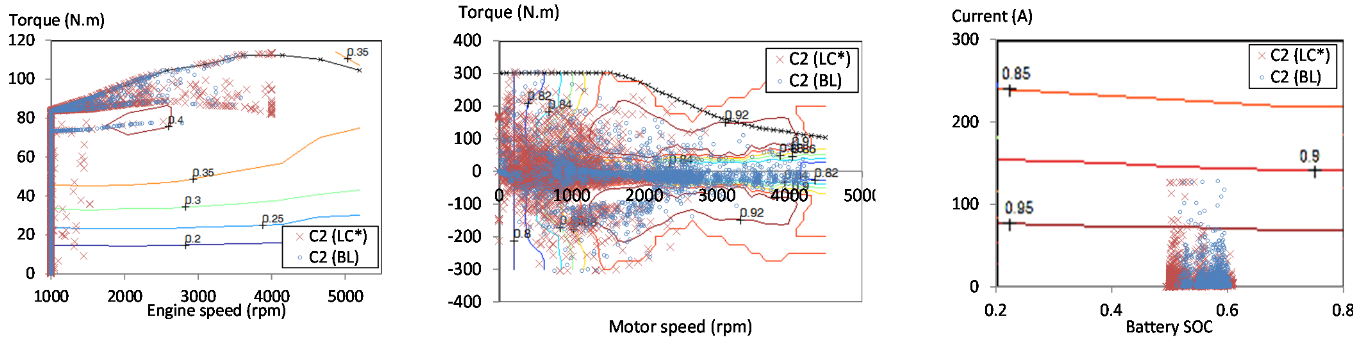
(**a**) (**b**) (**c**)

Figure A3. Plots of B3 solution engine (**a**), electric motor (**b**), and battery (**c**) operation for BL and LC driving cycles. (* driving cycle used in the optimization).



(**a**) (**b**) (**c**)

Figure A4. Plots of C1 solution engine (**a**), electric motor (**b**), and battery (**c**) operation for BL and LC driving cycles. (* driving cycle used in the optimization).



(**a**) (**b**) (**c**)

Figure A5. Plots of C2 solution engine (**a**), electric motor (**b**), and battery (**c**) operation for BL and LC driving cycles. (* driving cycle used in the optimization).

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