Real CO2 emissions benefits and end user's operating costs of a plug-in Hybrid Electric Vehicle

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Real CO_2 emissions benefits and end user's operating costs of a plug-in Hybrid Electric Vehicle

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HIGHLIGHTS

- Real CO_2 emissions of a plug-in Hybrid Electric Vehicle analyzed.
- Impact on CO_2 emissions of the engine efficiency and of the energy source mix highlighted.
- Minimization of the overall CO_2 emissions also achieves the minimum of the energy cost.

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ABSTRACT

Although plug-in Hybrid Electric Vehicles (pHEVs) can be considered a powerful technology to promote the change from conventional mobility to e-mobility, their real benefits, in terms of CO_2 emissions, depend to a great extent on the average efficiency of their Internal Combustion Engine and on the energy source mix which is used to supply the electrical demand of pHEV.

Furthermore the operating cost of the vehicle should also be taken into account in the design process, since it represents the main driver in the customer's choice.

This article has the purpose of assessing, through numerical simulations, the effects of different technology mixes used to produce electrical energy for the battery recharging, of different Internal Combustion Engines on the pHEV performance, and highlighting the main differences with respect to the regulatory test procedure.

1. Introduction

Increasing concern about greenhouse effects has led the United Nations Intergovernmental Panel on Climate Change (IPCC) to conclude that a reduction of at least 50% in global CO_2 emissions, compared to the 2000 levels, has to be achieved by 2050, in order to limit the long-term rise in the global average temperature [1]. Although this target has been set for all sources of CO_2 emissions, the transportation sector, which is responsible for 33% of carbon dioxide emissions [2], unlike most of the other sectors, has shown an increase in total greenhouse gas emissions, which have been predicted to grow further in the coming years [3], due to the expansion of the global vehicle fleet. In this framework electrification of the powertrain could represent a valuable solution since Electric Vehicles (EVs) do not generate pollutants at a local level and can potentially rely on energy from a selection of renewable sources.

Nevertheless, despite continuous developments in battery technology, the costs, range capability and long recharging time are still considered barriers to the widespread adoption of such vehicles [4]. Therefore, the increasing interest in combining the desirable features of Electric Vehicles with the range capability of conventional vehicles, has led to the investigation of plug-in Hybrid Electric Vehicles (pHEVs) which can offer drivers the same range as conventional Internal Combustion Engines but can also lead to the environmental benefits of Electric Vehicles for short distances [5–7]. pHEVs shift a portion of the emission burden of automobile travel from on-road fossil fuel combustion to electricity generation at stationary power plants, and, although the European regulation exempts CO_2 production related to battery recharging in order to foster the diffusion of such vehicles, the impact of this shift on the overall CO_2 emissions depends on the average efficiency of the Internal Combustion Engine, on the amount of the electricity required from the grid and on the mix of energy sources used to satisfy the pHEV electrical demand. Therefore the real CO_2 benefits that could be achieved by pHEVs deserve a careful

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Nomenclature

C	cost
D	distance
E	energy
M	consumed mass
$\dot{m}_f$	fuel mass flow rate
ρ	density
μ	molar mass
T	time
u	control variable

Subscripts

AV	average
BATT	battery
E	electric
ELEC	electricity
F	fuel

Abbreviations

APU	Auxiliary Power Unit
ARTEMIS	Assessment and Reliability of Transport Emission Models and Inventory Systems Driving Cycle
CIE	Carbon Intensity of the Electricity
DP	Dynamic Programming
HEV	Hybrid Electric Vehicle
ER	Extended Range
EUDC	Extra Urban Driving Cycle
EV	Electric Vehicle
FTP75	Federal Test Procedure
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
NEDC	New European Driving Cycle
NVH	Noise Vibration Harshness
PHEV	plug-in Hybrid Electric Vehicle
SOC	State of Charge
UDC	Urban Driving Cycle
US06	United States Supplemental Federal Test Procedure
WLTP	Worldwide Harmonized Light Duty Test Procedure

analysis. However, such an investigation has so far only partially been carried out and reported in the scientific literature (see for instance [8]), which has been until now mostly focused on the analysis of charge sustaining HEVs.

Moreover, not only CO_2 emissions, but also the operating cost of the vehicle should be taken into account in the definition of the vehicle targets since it is one of the main drivers in the customer's choice and it depends to a greater extent on both fuel and electricity costs.

For the abovementioned reasons, this article describes the effects of different Internal Combustion Engines and different energy mixes used to produce the electricity required to recharge batteries, on the performance of a case study pHEV with the aim of minimizing its overall CO_2 emissions and of highlighting the gap between its real emissions and the value calculated through the regulatory test procedure. Furthermore, this approach is compared with an alternative methodology that is focused on the minimization of energy costs.

After a brief introduction to the methodology (Section 3), the paper presents the main features of the case study hybrid architecture (Section 4) and the reference performance achieved with a control strategy that is focused on the minimization of the overall CO_2 emissions (Section 5.1). The main findings of the sensitivity analysis, performed on both technology mixes used to produce electricity to recharge batteries (Section 5.2) and on the main powertrain components (Section 5.3) are then presented. Finally, the main differences between the CO_2 minimization and the cost minimization strategies are pointed out (Section 5.4).

2. Methodology

The main advantage of using a Hybrid Electric Vehicle is the additional degree of freedom that can be obtained due to the presence of an additional energy reservoir – the electric battery – besides the fuel tank [9]. This implies that, at each instant of time, the power needed by the vehicle can be provided by either one of these sources, or by a combination of the two. The choice from among all the available powersplit combinations depends on the actual objective of the hybridization, which can usually be defined as the minimization of a given cost function. This process represents a typical optimal control problem [10] that can usually be addressed through several methodologies which can differ in performance, computational requirements and computational efforts [11,12]. Since the definition of an energy management system is not the scope of this article, the authors used a global optimization algorithm, the Dynamic Programming algorithm [13,14], to set the ideal performance for the case study hybrid architecture and to highlight the effects of some parameters on vehicle performance.

The Dynamic Programming (DP), generates a numerical solution for an optimal control problem and it gives sufficient conditions for the global optimality. It is based on Bellman's principle of optimality [10] and is able to manage a dynamic model of the system; since DP is commonly used to solve time-continuous control problems, the model has to be discretized in a sequence of time steps for which DP is capable of determining the optimal control laws. The optimal cost-to-go function (see Eq. (1)) is then computed for each value of the state variables (for instance the State Of Energy – SOE of the battery) in the admissible range following a backward path starting from the final time and state as depicted in Fig. 1a. Then, once the backward iterations have been completed, the law that generates the optimal cost-to-go value is defined for each time step and is used to compute the optimal control sequence through a forward iteration of the algorithm (see Fig. 1b). Even though the need for a backward procedure means that the solution can be obtained only offline, for a driving cycle known a priori, and therefore is not implementable on a real vehicle, the optimal control law can be used to gather information for the development of simpler and implementable strategies and to benchmark their performance [15,16].

All the analyses presented in this paper were carried out through numerical simulations performed on a vehicle model developed in Matlab environment. This model relies on a kinematic approach [17,18] based on a backward methodology where the input variables are the speed of the vehicle and the grade angle of the road (see Fig. 2). The powertrain speed can then be easily determined from simple kinematic relationships, starting from the wheel revolution speed and the total transmission ratio of the driveline, while the traction force that should be provided to the wheels to drive the vehicle according to the chosen speed profile can be calculated from the main vehicle characteristics (i.e. vehicle mass, aerodynamic drag and rolling resistance). Both the Internal Combustion Engine and the electric machines are represented through performance maps that were experimentally

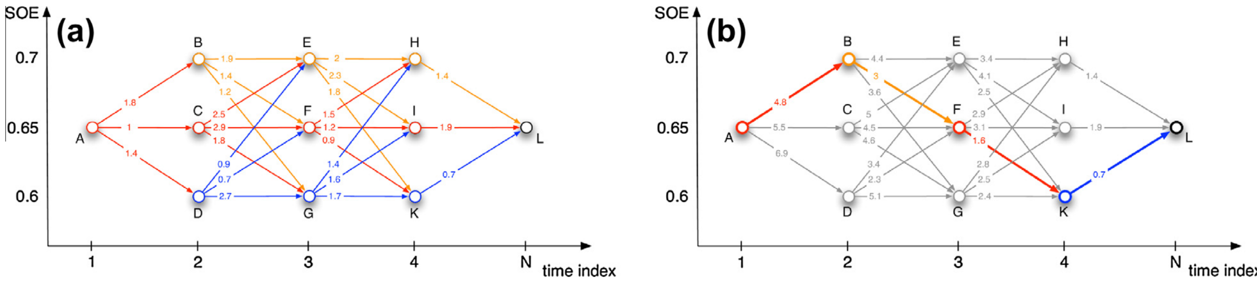

Fig. 1. Dynamic Programming algorithm: study of the possible patterns (a); selection of the pattern related to minimum fuel consumption (b) [12].

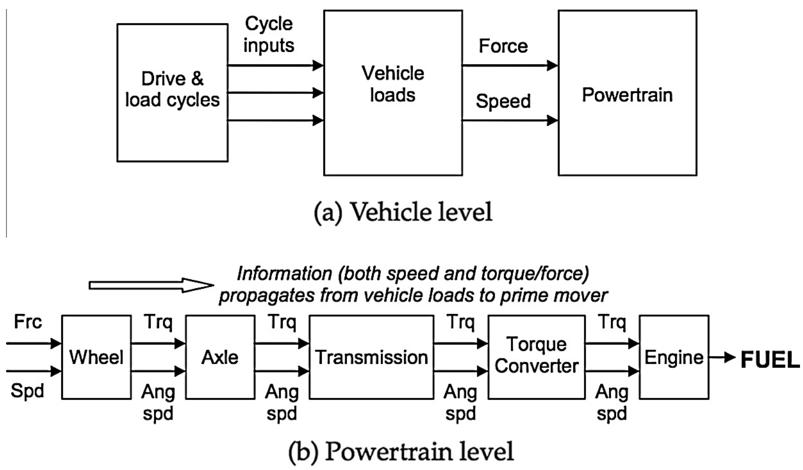

Fig. 2. Information flow in a kinematic or backward simulator [19].

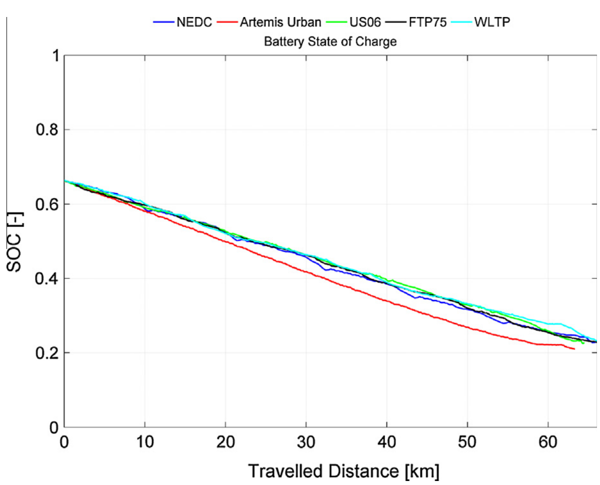

Fig. 3. Battery State of Charge (SOC) profile vs. traveled distance for different driving cycles (NEDC, Artemis, US0, FTP75, WLTP).

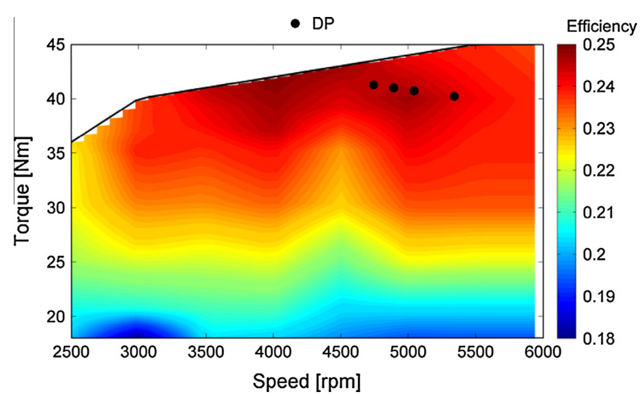

Fig. 4. Engine Operating points selected by the Dynamic Programming (DP) represented on its efficiency map.

measured under steady state operating conditions (see Fig. 4 for an example).

Obviously this approach neglects all the dynamic phenomena considering transient conditions as a sequence of stationary states. Furthermore, because of its backward approach, it assumes that driving profile will be exactly followed, providing no guarantees that a given vehicle will actually be able to meet the desired speed trace, since the power request is directly computed from the speed and it is not checked vs. actual powertrain capabilities [19]. Despite its simplicity, such an approach has proved to be appropriate [20–22] for the calculation of the instantaneous fuel consumption over the most common regulatory driving cycles, due to the moderate speed and load transients that are usually prescribed.

3. Case study

The case study selected for this study is a pHEV featuring a series architecture [23] integrated in a mid-size European passenger car, the main specifications of which are represented in Table 1. This architecture was selected since it represents one of the most promising solutions to overcome the limitations of an electric powertrain that combines the desirable features of an Electric Vehicle with the range capability of a conventional vehicle [4,24,25]. Indeed, it can operate in full electric mode (which will be referred to hereafter as "EV mode") with the APU switched off

Table 1
Basic specifications of the pHEV.

Vehicle		
Mid-size European passenger car		
Mass (kg)	1600	
Frontal area (m^2)	2.42	
Drag coefficient (–)	0.48	
Road load @100 km/h (kW)	18	
Powertrain		
Electric motor	Permanent magnet	
	Peak power (kW):	60
	Peak torque (Nm):	280
	Base speed (RPM):	2000
	Peak efficiency (–):	0.96
Battery	Li-ion	
	Energy (kW h):	24.4
	96 series cells – 4 parallel modules	
Range extender unit	S.I. unconventional engine:	
	Max power (kW):	30
	Peak efficiency (–):	0.25
	Permanent magnet electric generator	
	Peak power (kW):	45

until the battery charge has not reached a minimum level. Whereupon, the vehicle reaches the final destination operating the powertrain in the so-called "series mode", in which the Internal Combustion Engine provides the energy required to keep the battery in charge sustaining conditions.

The selected hybrid architecture was already extensively described in a previous work of the authors [26] and only its main characteristics will be recalled hereafter for sake of brevity.

The vehicle is equipped with a permanent magnet electric motor of about 60 kW@2000 RPM directly connected to the front axis through a fixed gear and powered by a Li-ion battery made up of 4 parallel modules of 96 cells connected in series which results into a total energy of about 25 kW h. Furthermore, the range extender unit consists of an unconventional small displacement spark ignition engine and of a permanent magnet electric generator.

Although the energy management strategies for Hybrid Electric Vehicles (HEVs) are generally developed with the primary target of reduce fuel consumption, such an approach may not be suitable for plug-in architectures since it neglects the energy consumption related to the battery, which cannot be considered an energy buffer, like in a charge sustaining HEV [9], but is, instead, an additional energy source that has to be recharged from the power grid. A possible way of taking both contributions into account is to minimize the overall CO_2 emissions of the vehicle. As shown in Eq. (1), besides considering the CO_2 produced by the engine, a second term related to the battery discharge and to the technology mix used to produce the electricity supplied by the grid is also considered:

$$J = \frac{\mu_{CO_2}}{\mu_{fuel}} \int_0^T \dot{m}_f(t, u(t))dt + \frac{1}{\eta_{chg} \cdot \eta_{grid}} \cdot CIE \cdot \Delta SOC \cdot E_{batt} \quad (1)$$

where J is the cost-to-go function, μ_{CO_2}, and μ_{fuel} are the molar mass of CO_2 and fuel respectively, $\dot{m}_f$ is the instantaneous fuel consumption of the engine, $u(t)$ is the vector of the control variables, T is the duration of the vehicle mission, η_{chg} is the average battery charging efficiency, η_{grid} is the transmission and distribution efficiency of a typical grid, Carbon Intensity of the Electricity (CIE) is the average CO_2 emission related to the production of the electrical energy that is supplied by the grid to recharge the battery, ΔSOC is the variation of the State of Charge from the beginning to the end of the vehicle mission, and E_{batt} is the total electrical energy that can be stored in the battery.

As far as batteries charging and grid efficiencies are concerned, according to the data reported in literature [27,28] grid transmission and distribution losses were estimated to be equal to 6% of the generated electrical power, while for the lithium batteries considered in this work, a charging efficiency equal to 86% was considered [29].

Moreover, the minimization of the cost function should also take into account some additional constraints (i.e. drivability, actuator limitations, thermal behavior, Noise, Vibration, and Harshness-NVH) and should ideally consider the entire life cycle of the vehicle. Nevertheless, in practical cases, the optimization horizon is finite and usually coincides with a short trip: according to several studies [30], about 70% of the daily driving distances in Europe does not exceed 50 km, and could therefore be covered by pure Electric Vehicles. However, a reference trip length of about 70 km was considered in this study with the aim of satisfying most of the customers' requirements (about 90% in Europe).

4. Results and discussion

This section presents the main findings of the study: in the first part the reference performance of the vehicle is established and the differences between the real emissions and the values calculated according to the procedure, which is prescribed by the European regulations are highlighted. Then, both the CIE and the Auxiliary Power Unit (APU) are changed in order to point out their effects on vehicle performance. Finally, the energy management strategy selected by the Dynamic Programming in a cost-oriented optimization is compared with the reference set by the CO_2 minimization.

4.1. CO_2 emission minimization target

The first set of simulations was performed assuming a value of 326 g/kW h for the CIE (see Eq. (1)) as representative of the average for the European countries belonging to the Organization for Economic Co-operation and Development (OECD) for the year 2009 [30] (see also Table 4). Taking into account the η_{grid} and η_{chg} values previously specified, this leads to an overall Carbon Intensity of the Electricity, including grid and charging losses, equal to 400 g/kW h.

The aim of this analysis was to define the optimal control strategy for several driving schedules, which were obtained through the repetition of standard driving cycles (such as NEDC, FTP, WLTP and Artemis Urban [31]) until a target trip distance of 70 km was obtained. The analysis of the collected data highlighted that Dynamic Programming manages the powersplit and achieves a linear discharge of the battery [32], regardless of the mission profile, as depicted in Fig. 3.

These results represent the optimal solution for the energy management of pHEVs operating in charge depleting mode, as already highlighted in scientific literature for different hybrid architectures [33,34,26].

Fig. 4 shows the Internal Combustion Engine operates within its best efficiency region.

As a result, the vehicle is able to achieve CO_2 emissions which are significantly lower than the target value of 95 (g/km) set by the European community on the NEDC driving cycle (see Table 2).

It is worth pointing out that the previous analysis takes into account the contributions due to both the Internal Combustion

Table 2
CO_2 emissions of the p-HEV for different driving cycles.

	CO_2 emissions (g/km)			
	Engine	Battery	Total	Regulatory EC test procedure
NEDC	15	64	79	34
WLTP	41	61	102	43
Artemis Urban	25	70	95	–
FTP75	12	62	74	–

Engine and battery recharging, while the specific test procedure prescribed by the European Commission for plug-in hybrid vehicles [35] mainly considers the CO_2 produced by the engine, while the CO_2 related to the electricity used to charge the battery is only partially taken into account. The European Union (EU) procedure requires two tests:

- *Condition A*: which is carried out on a single driving cycle with a fully charged electrical energy storage device.
- *Condition B*: which is carried out on a single driving cycle with the electrical energy storage device in the minimum State of Charge.

Consequently the actual CO_2 emissions of the vehicle are represented by the weighted average of the data recorded in the previous tests and the weights are the vehicle electric range and the average distance between two battery recharges (see Eq. (2)).

$$M = \frac{D_e \cdot M_1 + D_{av} \cdot M_2}{D_e + D_{av}} \tag{2}$$

where M_1 and M_2 (g/km) are the CO_2 emissions recorded in conditions A and B respectively, D_e is the electric range of the vehicle (the distance covered in EV mode on the considered cycle or its multiple) and D_{av} is the average distance between two battery recharges (which is assumed to be about 25 km).

The performance shown in Table 3 were achieved by applying this procedure to the test pHEV architecture.

It can be observed that such a procedure emphasizes the pHEV performance since, during condition A, there is no CO_2 production: the Dynamic Programming, in fact, only exploits the EV mode thanks to the huge amount of energy stored in the battery. Consequently, if the CO_2 emissions due to the battery recharge phases are taken into account as in the proposed methodology, differently from the standard regulatory procedure, the pHEV CO_2 emissions result to be significantly higher, although still remarkably lower than those of a conventional vehicle. For instance the type approval procedure for CO_2 emission calculation for NEDC, would lead to a 34 g/km figure for the test vehicle, while, when the CO_2 emissions related to the battery recharge are also accounted for, it leads to a 79 g/km (see Table 2). A similar behaviour can also be observed for the WLTP cycle, although the higher power demand over the cycle leads to a more intense use of the Internal Combustion Engine and therefore to higher CO_2 emissions.

4.2. Sensitivity analysis of the CIE

As already mentioned in the introduction, the energy management system defined by the Dynamic Programming may change significantly depending on the cost of the electrical energy, which is calculated through the coefficient CIE (See Eq. (1)). A study by the International Energy Agency (IEA) [30] has revealed that the CO_2 emissions related to electricity production depend to a great extent on the considered geographical region: the values can vary from 90 g/kW h (e.g. for France, where a significant fraction of the electrical energy is produced through nuclear power plants), up to about 1000 g/kW h in emerging countries (see Table 4).

Therefore, a sensitivity analysis in the 70 to 1000 g/kW h range was carried out, in order to analyze the effect of this parameter on the energy management system.

The SOC profiles on the NEDC represented in Fig. 5 show that, as expected, the increase of the CIE implies a lower use of the energy stored in the battery. Globally the increase of both the CIE and the higher engine usage also produces a deterioration of the overall emission of the vehicle (see Table 5). However, significant changes in the control strategy can only be appreciated when the CIE related to the electricity production reaches its maximum values. The reason for this trend, is related to the low efficiency of the engine which generates a significantly higher CO_2 specific emission (about 1000 (g/kW h)) compared to the average CIE of industrialized countries (about 450 (g/kW h)). This behavior is also reflected in the final State of Charge of the battery shown in Table 5: the battery usage is almost the same until its weight on the CO_2 production is lower than the ICE contribution, while the battery depletion suddenly decreases when its impact on the total CO_2 emissions becomes comparable to or higher than the ICE CO_2 production rate.

Table 3
CO_2 emissions of the test pHEV calculated through the procedure prescribed by the European Commission regulation [34].

	Condition A				Condition B			
	Final SOC	D_{test1} (km)	D_e (km)	M_1 (g/km)	Final SOC	D_{test2} (km)	D_{av} (km)	M_2 (g/km)
NEDC	0.91	11	109	0	0.25	11	25	184
WLTP	0.8	23	90	0	0.25	23	25	200

Overall results
$M = \frac{D_e \cdot M_1 + D_{av} \cdot M_2}{D_e + D_{av}}$

	M (g/km) CO_2
NEDC	34
WLTP	43

Table 4
CIE (gCO_2/kW h) of different countries in recent years [28].

	2003	2004	2005	2006	2007	2008	2009	Average 07–09
World	495	500	500	503	508	504	500	504
US	571	571	570	542	549	535	508	531
Japan	444	427	429	418	452	438	415	435
France	81	79	93	87	90	87	90	89
Germany	434	436	406	404	468	441	430	447
Italy	511	459	449	468	440	421	386	416
The United Kingdom	478	486	485	507	499	490	450	480
OECD Europe	358	351	343	348	357	340	326	341
China	776	804	787	787	758	744	743	748
India	892	931	923	921	943	954	951	950

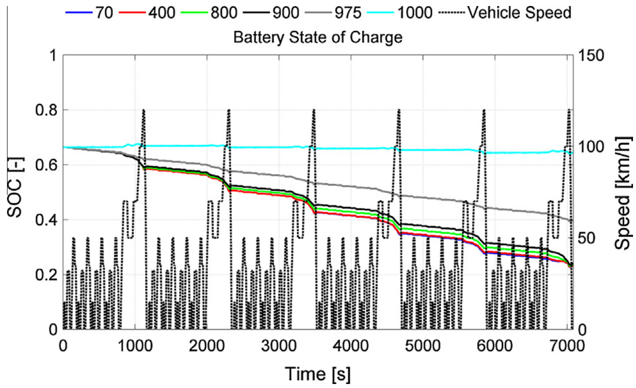

Fig. 5. Variations in the SOC profile obtained by means of the DP depending on the CIE levels (varying from 70 to 1000 g/kW h) – Several repetitions of the NEDC driving cycle.

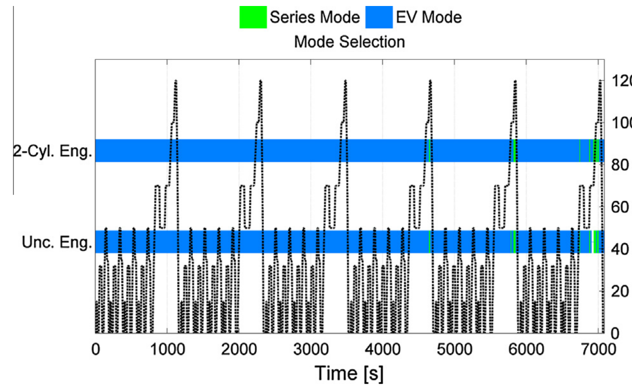

Fig. 7. Comparison of the operating modes of the hybrid powertrain between unconventional and reciprocating 2 cylinder engine over a sequence of NEDCs.

4.3. Sensitivity analysis of the auxiliary power unit

On the basis of the main requirements of the range extender module defined in [25], the APU selected for this application features a non-conventional Internal Combustion Engine (ICE) in order to ensure advantages in terms of packaging, weight and NVH behaviour. However, this decision leads to an engine with a lower average efficiency than conventional reciprocating engines (as shown in Fig. 6). Nevertheless, since a proper design of the range extender unit could reduce the gap in terms of NVH and packaging [4–24], the performance of a high efficiency 2 cylinder in-line spark ignition engine has been investigated and compared with the reference component.

The simulations were run on the reference distance of 70 km, focusing on the effects on the vehicle CO_2 emissions of the efficiency of the Internal Combustion Engine.

The comparison of the operating modes represented in Fig. 7 shows that the criteria that enable the series mode are almost the same. On the other hand, once the engine is on, the APU equipped with the 2-cylinder engine provides less power to support the battery (see Fig. 8).

This choice is related to the efficiency of the 2 cylinder engine, which reaches its maximum at a lower speed: Dynamic Programming reduces the power in order to minimize fuel consumption and consequently increases the engine-on time in order to provide the same energy to the wheels.

The efficiency improvements in the reciprocating engine highlighted in Fig. 9, lead to significant reductions in the CO_2 emissions (see Table 6). Moreover, the enhancement significantly increases if the battery is almost fully depleted and the vehicle spends more time in series mode, as demonstrated by the column on the right in Table 6.

4.4. Alternative cost function: energy cost

Although customers are currently more and more aware of the relevance of global warming, they generally believe that a Hybrid Electric Vehicle should above all reduce fuel expenditure. Therefore, an additional analysis has been performed taking into account the energy cost as the performance index. As for the CO_2 emissions

Table 5
Main findings of the sensitivity analysis on the CIE (test performed on six repetitions of the NEDC).

	70 (g/kW h)	400 (g/kW h)	800 (g/kW h)	900 (g/kW h)	975 (g/kW h)	1000 (g/kW h)
Final SOC (–)	0.23	0.23	0.23	0.24	0.40	0.64
APU Energy (kW h)	0.92	0.93	0.99	1.02	4.5	9.9
Total CO_2 Emission (battery + engine) (g/km)	26	79	143	159	170	171

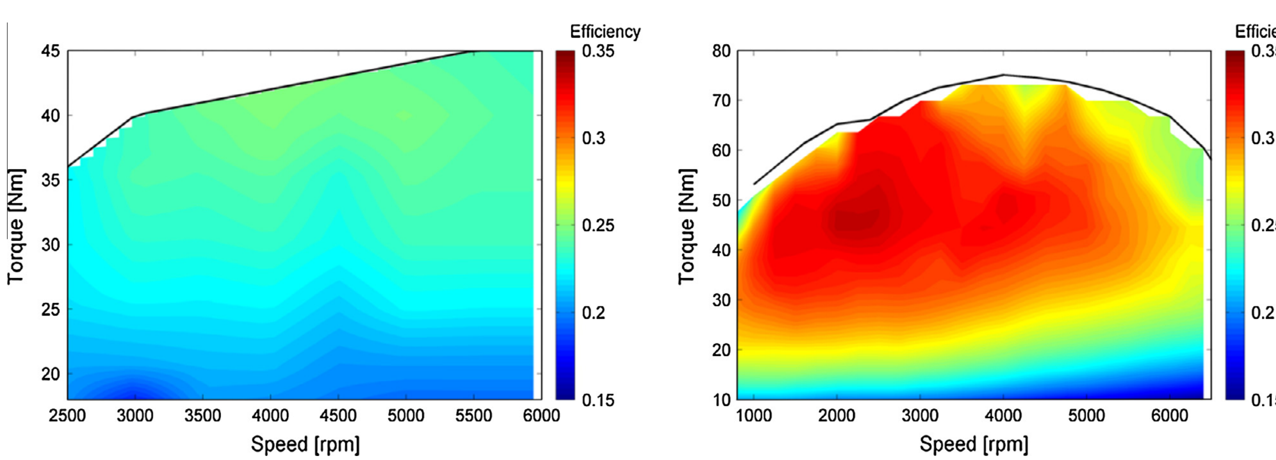

Fig. 6. Comparison between the efficiency maps of an unconventional engine (left) and a reciprocating (right) engine.

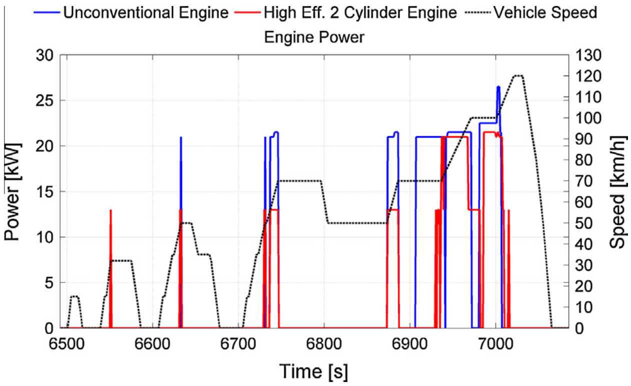

Fig. 8. Comparison between the power provided by the unconventional and by the reciprocating 2 cylinder engine over a sequence of NEDC (enlarged view of the last NEDC segment).

the cost function is composed of two parts: the first is related to the fuel, while the second is related to the electrical energy required to recharge the battery (see Eq. (3)):

$$J = \frac{C_{fuel}}{\rho_{fuel}} \int_0^T \dot{m}_f(t, u(t))dt + \frac{1}{\eta_{chg}} \cdot C_{elec} \cdot \Delta SOC \cdot E_{batt} \quad (3)$$

where C_{fuel} and C_{elec} represent the fuel and electricity costs respectively, and which, in both case, were assumed equal to the 2010 European average [36,37] (see Fig. 10).

From the analysis of Fig. 11 it can be seen that no significant change is clearly visible in the decisions taken by Dynamic Programming when the cost is the target instead of CO_2 emissions: almost negligible differences appear in the power provided by the APU during EUDC but they do not affect the overall performance of the vehicle, as demonstrated by the results shown in Table 7.

The lack of any significant differences between the results obtained for the two different optimization targets is related to the specific cost of the fuel, which is significantly higher than the electricity cost (0.56 (€/kW h) for the fuel vs. 0.171 (€/kW h) for the electricity). Therefore, since the ratio between these costs (about 3.3) is quite close to the ratio between the specific CO_2

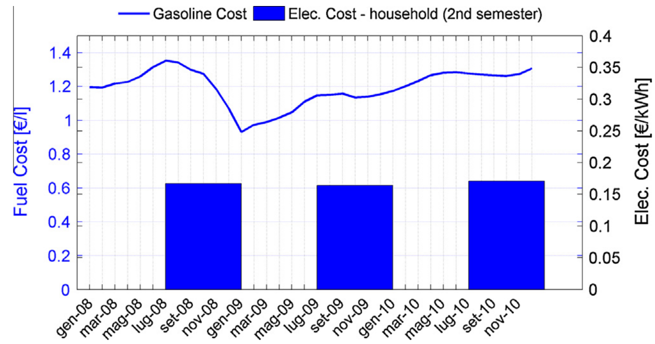

Fig. 10. Fuel and electricity costs trends in the recent years.

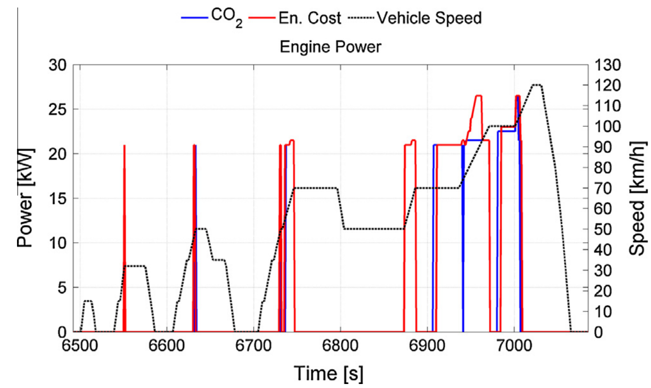

Fig. 11. Comparison between the power provided by the APU over one of multiple repetitions of NEDCs in the case of CO_2 minimization and in the case of cost minimization.

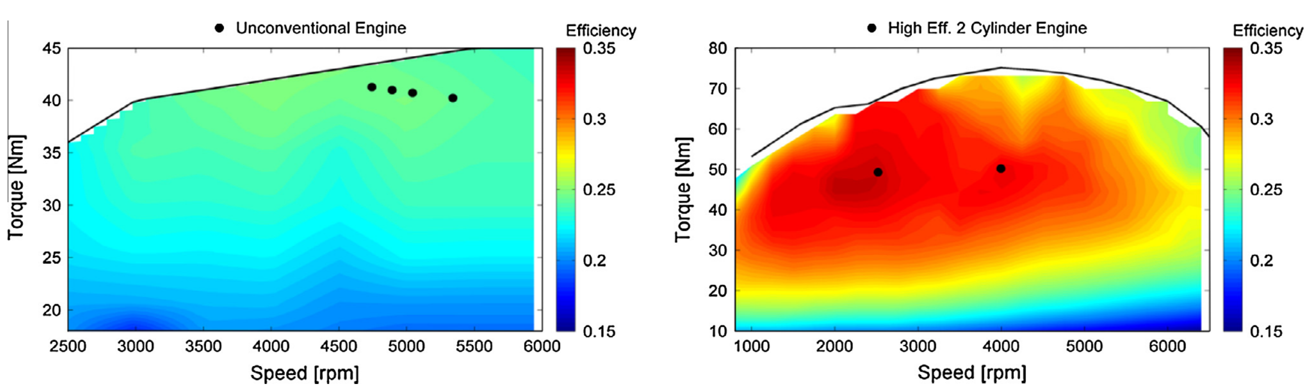

Fig. 9. Comparison on the efficiency maps of the engine operating points over a sequence of NEDCs. Left: unconventional Engine; Right: 2 cylinder engine.

Table 6
CO_2 emissions of the 2 cylinder engine for different driving cycles (the Δ variation refers to results obtained with the *unconventional* engine).

CO_2 emissions (g/km)	Charged battery Repeated cycles for 70 km			Battery depleted Single cycle		
	Unconventional. engine	2-Cyl engine	Δ%	Unconventional engine	2-Cyl engine	Δ%
NEDC	79	73	8	171	121	29
WLTP	106	93	12	196	141	28
Artemis Urban	95	87	8	195	137	30

Table 7
Comparison of CO_2 emissions and energy costs for different driving cycles for two different optimization strategies (cost minimization left, CO_2 minimization right).

	End user cost minimization target						CO_2 minimization target					
	End user cost (€)			CO_2 emission (g/km)			End user cost (€)			CO_2 emission (g/km)		
	Fuel cost	Elec. cost	Total cost	CO_2 engine	CO_2 grid	Total CO_2	Fuel Cost	Elec. Cost	Total Cost	CO_2 engine	CO_2 grid	Total CO_2
NEDC	0.57	2.09	2.66	16	64	80	0.56	2.09	2.65	15	64	79
Artemis Urban	0.87	2.20	3.07	25	70	95	0.88	2.20	3.08	25	70	95
FTP75	0.45	2.19	2.64	12	62	74	0.45	2.19	2.64	12	62	74
WLTP	1.53	2.17	3.70	42	64	106	1.50	2.19	3.69	40	65	105

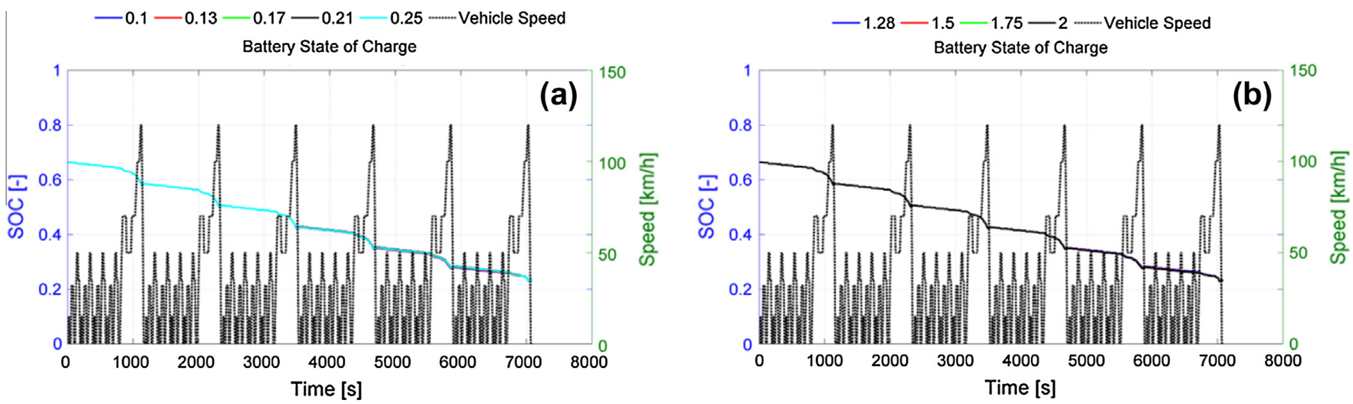

Fig. 12. Variations in the SOC profile obtained by means of the DP on multiple NEDCs: (a) for different electricity costs ranging from 0.1 to 0.25 (€/kW h) (and fuel cost equal to 1.28 (€/L)) – (b) for different fuel costs ranging from 1.28 to 2 (€/L) (and electricity cost equal to 0.17 (€/kW h)).

engine emissions and the electricity production related to the battery recharge (about 3.5), the control laws defined by Dynamic Programming for the two different targets cannot be significantly different.

As a result, it can be stated that by implementing a strategy aimed to minimize the CO_2 emissions of the vehicle, it is possible to simultaneously obtain the minimum energy cost for the end user.

Obviously, the trend of the price ratio between electricity and fuel can vary in the future depending on changes in the energy sources mix used for the electricity production as well as to unpredictable factors connected to the oil availability. Therefore two further parameter sweeps, for the electricity and fuel costs respectively, were also performed to point out possible changes in the energy management strategy. Both parameter sweeps were executed keeping fixed all the other parameter values.

The obtained results are shown in Fig. 12, limiting for sake of brevity to the SOC vs. time pattern, i.e. showing how the energy management strategy exploits the battery energy depending on the costs of fuel and electricity.

The results of the electricity cost sweep are shown in Fig. 12.a, for a variation range equal to 0.1–0.25 (€/kW h), while the results of the fuel cost sweep are shown in Fig. 12.b, for a variation range equal to 1.28–2 (€/Liter) (corresponding to a 0.56–0.89 (€/kW h) range). It is pretty clear that no significant variations in SOC trends and therefore in battery energy exploitation can be appreciated: in both cases the price of the electricity always remains well below the fuel cost. Therefore, the final cost of the trip will vary, but the usage of the battery will remain the preferred option for the energy management strategy.

In conclusions, the main finding of this energy cost analysis, i.e. that by implementing a strategy aimed to minimize the CO_2 emissions of the vehicle, it is possible to simultaneously obtain the minimum energy cost for the end user, is likely to be confirmed also in the future at least for reasonably foreseeable fuel and electricity price variations.

5. Conclusions

This article presents an overview of the effects of some optimization parameters on the performance of a case study pHEV featuring a series architecture and highlights the gap between the real CO_2 emissions of the vehicle and the values obtained with the calculation procedure prescribed by the European regulation.

The starting point was the definition, through a global optimization algorithm, of a powertrain control strategy with the aim of minimizing the overall CO_2 emissions of the vehicle. Such an approach pointed out the relevance of CO_2 related to battery recharging from the grid which, however, is neglected by the European regulation in order to foster the introduction of Electric Vehicles on the car market.

Furthermore the performance index based on the overall CO_2 emissions of the vehicle has shown to be able to also achieve the minimum of the energy cost which is the most important parameter from the customer's point of view: in both minimization processes, the use of the engine was in fact shown to be significantly more expensive than the battery discharging. This finding was also strengthened by the sensitivity analysis on the CIE, which showed negligible effects on the control law defined by Dynamic Programming when typical data from industrialized countries such as the US, EU and Japan, were used (appreciable effects could only be observed for very high CIE, which are typical of China and India).

Finally the use of a high-efficiency Internal Combustion Engine for the APU led to major improvements in CO_2 emissions (especially for real world driving conditions) compared to an unconventional engine which was designed to minimize packaging, weight and NVH behaviour.

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References

[1] International Energy Agency. Energy technology perspectives 2010 – Scenarios & strategies to 2050, ISBN 978-92-64-08597-8. Paris: July; 2010.
[2] Energy Information Administration, Annual energy outlook. <http://www.eia.doe.gov/oiaf/aeo/index.html>, 2010.
[3] Kampman B, Leguijt C, Bennink D, Wielders L, Rijkee X, De Buck A, et al. Green power for electric cars – development of policy recommendations to harvest the potential of Electric Vehicle. Delft; January, 2010.
[4] Warth M, Bassett M, Hall J, Korte V, Mahr B. Design and development of the MAHLE Range Extender Engine, paper presented at the Aachen Colloquia. Germany: Aachen; October 2011.
[5] Electric Power Research Institute, Environmental assessment of plug-in Hybrid Electric Vehicles; 2007.
[6] Stephan CH, Sullivan J. Environmental and energy implications of plug-inhybrid-Electric Vehicles. Environ Sci Technol 2008; 42(4): 1185–90, 2008.
[7] Kelly J, MacDonald J, Keoleian G. Time-dependent plug-in Hybrid Electric Vehicle charging based on national driving patterns and demographics, Appl Energy 2012;94:395–405. doi: 10.1016/j.apenergy.2012.02.001.
[8] Doucette RT, McCulloch MD. Modeling the prospects of plug-in Hybrid Electric Vehicles to reduce CO_2 emissions. Appl Energy 2011;88(7):2315–23.
[9] Paganelli G, Ercole G, Brahma A, Guezennec Y, Rizzoni G. General supervisory control policy for the energy optimization of charge-sustaining Hybrid Electric Vehicle. JSAE Rev 2001;22(4):511–8.
[10] Lewis FL, Syrmos VL. Opt Control. Wiley: Interscience; 1995.
[11] Lin CC, Peng H, Grizzle JW, Kang J., Power management strategy for a parallel hybrid electric truck. IEEE Trans Control Syst Technol. 2003; 11(6).
[12] Serrao L, A comparative analysis of energy management strategies for Hybrid Electric Vehicle PhD thesis. Columbus (Ohio, United States): The Ohio State University. 2009.
[13] Sundstrom O, Guzzella L, A generic Dynamic Programming matlab function paper presented at the 18th IEEE Int Conference Control Appl. 2009: pp. 1625–1630.
[14] Sundstrom O, Ambuhl D, Guzzella L. On implementation of Dynamic Programming for optimal control problems with final state constraints. Oil and Gas Science and Technology – Rev. IFP, doi: 10.2516/ogst /2009020, September, 2009.
[15] Bianchi D, Rolando L, Serrao L, Onori S, Rizzoni G, Al-Khayat N, et al. Layered control strategies for Hybrid Electric Vehicles based on optimal control. Int J Elect Hybrid Vehicles 2011.
[16] Bianchi D, Rolando L, Serrao L, Onori L, Rizzoni G, Al-Khayat N, Hsieh TM, Kang P. A rule-based strategy for a series/parallel Hybrid Electric Vehicle: an approach based on Dynamic Programming. 2010 ASME Dynamic Systems and Control Conference.
[17] Millo F, Rolando L, Andreata M. Numerical simulation for vehicle powertrain development. In: Numerical analysis – theory and application, AA.VV. 2011: pp. 519–540. ISBN 978-953-307-389-7.
[18] Bianchi D, Rolando L, Serrao L, Onori S, Rizzoni G, Al-Khayat N, et al. A rule-based strategies for a series–parallel Hybrid Electric Vehicle: an approach based on Dynamic Programming. Cambridge: ASME Dynamic Systems and Control Conference; 2010.
[19] Guzzella G, Sciarretta A. Vehicle propulsion systems: introduction to modeling and optimization. Berlin: Springer; 2007, ISBN 9783642094156.
[20] Millo F, Di Lorenzo G, Servetto E, Capra A. et al. Analysis of the performance of a turbocharged s.i. engine under transient operating conditions by means of fast running models, SAE Int. J. Engines 2013; 6(2): 968–978. doi:10.4271/2013-01-1115.
[21] Rolando L. An innovative methodology for the development of HEVs energy management systems. PhD thesis, Politecnico di Torino (Torino, Italy). 2012.
[22] Millo F, Rolando L, Servetto E. Development of a control strategy for complex light-duty diesel-hybrid powertrains. SAE Technical Paper 2011–24-0076. 2011. doi:10.4271/2011-24-0076.
[23] Genender P, Wolff K, Eisele G, Jung G. NVH development of an Electric Vehicle with range extender unit, paper presented at the conference NVH of hybrid & Electric Vehicles, Supméca (Saint-Ouen, France). 4 February 2010.
[24] Pischinger M, Wittek K, Genender P, Nysten F, Andert J, Esch H, et al. V2-range extender module with FEVcom – a barely noticeable companion in your Electric Vehicle, paper presented at the Aachen Colloquia. Germany: Aachen; October 2011.
[25] Rust A, Graf B. NVH of Electric Vehicles with range extender, SAE Int. J Passeng Cars – Mech Syst 2010;3(1):860–7. http://dx.doi.org/10.4271/2010-01-1404.
[26] Millo F, Rolando L, Mallamo F, Fuso R. Development of an optimal strategy for the energy management of a range-extended Electric Vehicle with additional noise, vibration and harshness constraints. IMechE J Automobile Eng Part D: J Automobile Eng 2013;227(1):4–16. http://dx.doi.org/10.1177/0954407012457488.
[27] ABB Inc.,Energy efficiency in the power grid. <http://www.abb.com/cawp/seitp202/64cee3203250d1b7c12572c8003b2b48.aspx> [accessed April 2013].
[28] ENEA, Quaderno: L'efficienza nel settore delle reti energetiche, Luglio 2011.
[29] Ulf Bossel. Reykjavik: Driving sustainability 2007.
[30] International Energy Agency – CO_2 Emissions from fuel combustion – HIGHLIGHTS 2011 EDITION.
[31] INRETS – Institut National de Recherche sur les Transports et leur Securite. Real-world driving cycles for measuring cars pollutant missions – Part A: The ARTEMIS European driving cycles. Report INRETS-LTE 0411 June 2004.
[32] Tulpule P, Marano V, Rizzoni G. Effects of different pHEV control strategies on vehicle performance, paper presented at the 2009 american control conference hyatt regency riverfront. MO (USA): St. Louis; June 2009.
[33] Larsson V, Johannesson L, Egardt B, Lassson A. (2012, June). Benefit of route recognition in energy management of plug-in Hybrid Electric Vehicles. IEEE. In: American Control Conference (ACC). 2012: p. 1314–20).
[34] Larsson V, Johannesson L, Egardt B. Impact of trip length uncertainty on optimal discharging strategies for pHEVs. In: Proceedings of the 6th IFAC Symposium Advances in Automotive Control. Munich: 2010, p. 55–60.
[35] Regulation No. 101 – rev. 2, United Nations Std. April 2005.
[36] EUROSTAT Energy. Transport and environment indicators. 2011.
[37] Europe's Energy Portal, Historical Fuel Price Data, 2011, <http://www.energy.eu/>.