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OPTIMIZATION-BASED CONTROLLERS FOR HYBRID ELECTRIC VEHICLES

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RESEARCH ARTICLE

ABSTRACT: Hybrid electric vehicles (HEVs) are more and more of interest in the present vehicle market, because of the relevant reduction both in the fuel consumption and in the CO_2 emission, in particular for the urban utilization. Different architectures are possible and have been considered for the vehicle hybridization. The most convenient architecture is depending on the application itself. This paper deals with a design methodology based on an optimization scheme to make the selection among the consistent number of alternatives. Optimization-based control strategies play a central role in the design process of HEVs. In early design phases they allow the comparison of different HEV powertrain architectures, thus supporting the selection of an appropriate topology. Furthermore, they lay the foundations for the development of real-time optimal energy management strategies to be implemented in the HEV on-board control unit. Fuel economy and design efficiency can overall be enhanced in this way. This paper aims at providing a comprehensive review of different optimization-based energy management strategies for HEVs. An analysis of strength and drawbacks of each considered strategy is carried out based on different evaluation criteria such as global optimality, computational cost and uniformity of the powertrain operation. Finally, simulation results for a HEV powertrain from the industrial state-of-art validate the conceptual and methodological comments related to the analysed controllers.

KEY WORDS: control optimization, fuel economy, hybrid electric vehicle, optimal design, powertrain modelling

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KOTROLERI ZASNOVANI NA OPTIMIZACIJI ZA HIBRIDNA ELEKTRIČNA VOZILA

REZIME: Hibridna električna vozila (HEV) su sve više interesantna za sadašnje tržište vozila, zbog značajnog smanjenja u potrošnji goriva i emisije CO_2 gasova, posebno u urbanom okruženju. Koriste se različite arhitekture za hibridizaciju vozila. Najprikladnija arhitektura zavisi od same primene. Ovaj rad se bavi metodologijom projektovanja zasnovanoj na šemi optimizacije koja bira između konzistentnog broja alternativa. Strategije upravljanja zasnovane na optimizaciji imaju glavnu ulogu u procesu projektovanja HEV. U ranim fazama projektovanja oni omogućavaju poređenje različitih arhitektura HEV pogona, čime se podržava izbor odgovarajuće koncepcije. Osim toga, postavili su temelje za razvoj optimalnih strategija za upravljanje energijom u realnom vremenu koje se primenjuju u HEV upravljačkoj jedinici. Na taj način se može poboljšati ekonomičnost potrošnje goriva i efikasnost rešenja. Ovaj rad ima za cilj da obezbedi sveobuhvatan pregled različitih strategija upravljanja energijom HEV-a zasnovanih na optimizaciji. Analiza prednosti i nedostatka svake razmatrane strategije urađena je na osnovu različitih kriterijuma za ocenu, kao što su globalni optimum, troškovi proračuna i uniformnost rada pogonske grupe. Na kraju, rezultati simulacije HEV pogonske grupe sa stanovišta razvoja tehnologije industrijske proizvodnje potvrđuju konceptualne i metodološke rezultate vezane za analizirane kontrolere.

KLJUČNE REČI: optimizacije upravljanja, ekonomičnost potrošnje goriva, hibridno električno vozilo, optimalan dizajn, modeliranje pogonske grupe

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1. INTRODUCTION

Regulations to reduce motor vehicle CO2 emissions and fuel consumption have been enforced worldwide recently [1]. This stringent trend is expected to be confirmed and even made more severe over the next decades. Vehicle producers have been subsequently pushed to employ new technologies, including the use of fully electrified powertrains. In this framework, hybrid electric vehicles (HEVs) are establishing as one of the most promising solutions to satisfy customer requirements and CO2 emission regulations at the same time. A HEV adds an additional power source (e.g. battery, ultra-capacitor, etc.) and one or multiple actuators (i.e. electric machines) to the conventional powertrain. The additional power devices help to improve system efficiency and fuel economy by engine right-sizing, load levelling, regenerative braking and pure electric mode.

To design a HEV, the engineer typically first selects one configuration to focus on. The vehicle design parameters (e.g. motor size, battery size, planetary gear sizes, etc.) and control strategy then need to be determined. Obviously, to achieve the near-optimal overall performance for the selected configuration, an iterative process needs to be executed. However, the problem for this approach is that even with this optimal performance, it is not known whether the selected configuration offers the best solution among all possible configurations. To achieve this goal, the exact same process, beginning from the selection of another configuration and then iteratively approaching the optimal performance, has to be repeated. Moreover, only when the optimal performance is gained for each configuration, then the comparison between them is a sensible task. With numerous options for the configuration design variations, such an iterative process can only be developed by means of a systematic method with many underlying techniques, including the automated model generation and simulation with optimal design and optimal control techniques. The many different possible configurations and additional propulsion components bring new challenge and research opportunities to vehicle designers. As several control problems reported in the literature, the control of HEVs can have a two level hierarchical architecture: the lower level control, and the supervisory control. For the lower level control, each subsystem (e.g. engine, electric motors, battery) is equipped with actuators, sensors and a control system to regulate its behavior, in response to the supervisory control commands. The design of lower level controllers can be separated from the supervisory controller, and it will not be considered in this paper. The supervisory control of the HEVs determines the operating mode and power levels of all power devices to balance design objectives such as drivability, fuel economy and battery health. The supervisory level control and its use in assessing the optimality of design candidates are the focus of this paper. This paper is organized as follows: the different architectures for an HEV and its design process are presented. The optimization-based control strategies for HEVs are subsequently illustrated and analyzed. A case study for the assessment of these strategies is then presented. Conclusions are finally given.

2. THE HEV DESIGN PROCESS

2.1 HEV powertrain architectures

To date three main categories are identified for a HEV architecture: series, parallel and power-split. The correspondent block diagrams are illustrated in Figure 1.

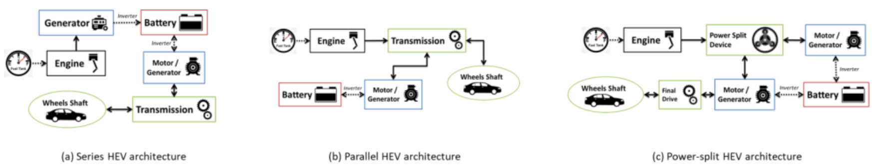

Figure 1. Different HEV architectures

2.1.1 Series HEV

In a series HEV, the propulsion is provided by one traction motor or more than one motors; the conventional engine drives the electricity generator, and they are both decoupled from the drivetrain. Since there is no mechanical coupling between the engine and vehicle drive axle, the engine speed and power are not rigidly constrained by the vehicle speed and road load, which enables the engine to operate always at high efficiency. In addition, because the traction motor usually can provide enough traction torque, transmission, in particular a gearbox, may not be needed. Despite simple and easy to control, the series hybrid vehicle powertrain suffers from high energy conversion losses: 100 % of the engine output must be converted into electrical power and some of it is further converted into electrochemical form and stored in the battery. The low efficiency is more pronounced when the vehicle is running in highway cruise or steady state because of double energy conversion (mechanical-electric-mechanical), while the series configuration is good for very transient drive cycles.

2.1.2 Parallel HEV

In a parallel HEV, both the electric Motor/Generator (MG) and the Internal Combustion Engine (ICE) can contribute to the propulsion directly. In other words, the engine torque and the electric motor torque are additive. When the MG is relatively small, it can only start/stop the engine, provide some regenerative power features, and drive the vehicle in limited circumstances; when the MG is large, it can drive the vehicle by itself or simultaneously with the engine. The MG can be used to shift the engine operating points to a higher-efficiency area by acting as a generator when the power demand is low or as a motor at high power demand. The efficiency of parallel hybrid vehicles can be very high on highways since the engine can directly drive the vehicle near its sweet spot and energy circulation between the mechanical energy and electric energy can be significantly reduced, while it reveals to be less convenient in transient driving cycles.

2.1.3 Power-split HEV

In a typical power-split HEV, an engine and two electric machines are connected to make a so-called "power-split device", represented by one or multiple planetary gear (PG) sets, through the carrier, the sun gear, and the ring gear. The lever diagram can be used to represent the 2 degrees of freedom dynamics of a PG, as illustrated in Figure 2.

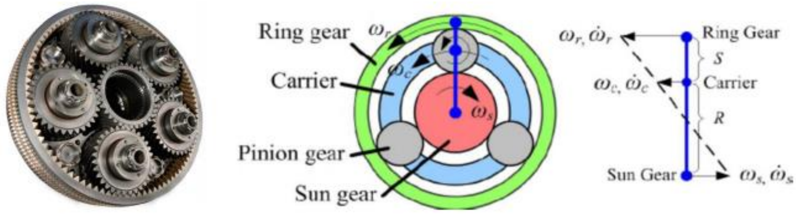

Figure 2. Planetary gear set and the lever diagram

The early power-split transmission appeared in the late 1960s and early 1970s, when such power-split mechanisms were used in lawn tractors. Although other early studies on power-split hybrid vehicles followed, at authors' best knowledge, in the market there was no passenger power-split hybrid vehicle until the Toyota Motor Corporation introduced the Prius, the first mass-production HEV in the world, in Japan in 1997 [2]. This hybrid powertrain system, called the Toyota Hybrid System (THS), is the framework and the foundation of all Toyota hybrid vehicles, as well as hybrid vehicles from several other companies, including the Ford Fusion Hybrid and the General Motor Allison Hybrid system [3]. Power-split hybrid vehicles are efficient in city driving conditions as a result of the pure electric drive function. However, due to energy circulation from the generator to the motor, the power-split vehicles may have higher energy losses than parallel HEVs in highway driving. This problem for single-mode power split hybrids can be avoided by adding clutch connections between different PG nodes, thus realizing multi-mode hybrid designs. Engagements and disengagements of clutch connections can enable different operating modes, thus improving the overall efficiency and performance of the system. Each operating mode typically best suits a specific case of vehicle operation (e.g. launching, accelerating, cruising at high speed, regenerative braking). Power-split architectures are the most successful and represent a large portion of the current population of HEVs. This paper particularly focuses on the power-split HEV powertrains with 2 PGs. A lever diagram for an example of this kind of system, taken from the industrial state-of-the-art, can be seen in Figure 3 [4]. The correspondent PG and final drive gear ratios are reported in the figure as well.

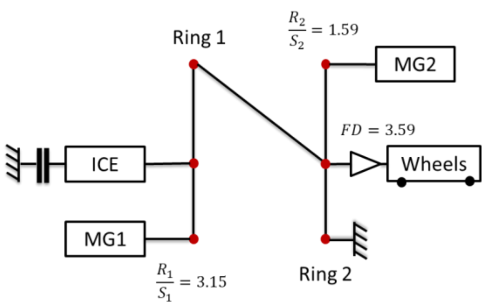

Figure 3. Example of a power split HEV

2.2 Modelling method for a power-split HEV

Many of today's power-split hybrid vehicles use two MGs to complement the ICE. In this paper, we only consider the case that each PG set is connected with two powertrain components, since having three powertrain components on the same PG will lead to very limited design flexibility. If we consider only the cases in which the engine and output shaft are on different PGs and each is complemented by a MG (inspired by Prius and GM Volt Gen 2), there are 144 possible configurations for components location. Three examples of configurations are reported in Figure 4.

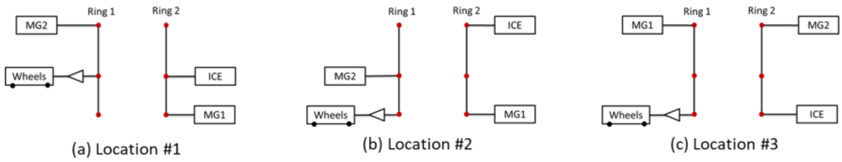

Figure 4. Examples of different components location for a 2 PG HEV

N_{clutch}, the total number of possible clutches, results to be 16. This value is found by using equation (1) and considering the number of PG sets (N_p) equal to 2. A correspondent graphical interpretation can be seen in Figure 5.

$$N_{clutch} = (C_{2N_p} - 2N_p) + 3N_p - 1 \tag{1}$$

The first parenthesized term (C_{2N_p}) represents the possible clutches added between each pair of nodes and corresponds to 15 for a double PG set. The second parenthesized term represents the redundant clutches to be eliminated. Since only one clutch could lock a planetary gear set by connecting any two nodes out of three in that planetary gear set, the other two possible connections are redundant (displayed in red in Figure 5). $3N_p$ represents the grounding clutches: all the gear nodes could be grounded except the one attached to output, eliminated by the last term.

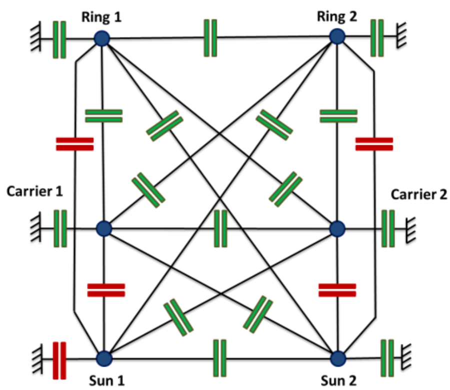

Figure 5. All possible clutch locations of a double PG HEV

Setting the maximum number of clutches to 3, this leads to generate 7280 different designs for each location of components. Therefore, the total number of candidate transmission designs (144x7280) for each set of input parameters is more than one million [5].

A methodology to model the modes of multi-mode HEVs was proposed in [6]. The dynamics of any specific mode is described by the characteristic matrix [A*], as shown in equation (2). This 4x4 characteristic matrix [A*] governs the relationship between the angular acceleration of powertrain components and their corresponding torques. The detailed derivations have been described by X. Zhang *et al.* in [6].

$$\begin{bmatrix} \dot{\omega}_{ICE} \\ \dot{\omega}_{OUT} \\ \dot{\omega}_{MG1} \\ \dot{\omega}_{MG2} \end{bmatrix} = [A^*] \begin{bmatrix} T_{ICE} \\ T_{OUT} \\ T_{MG1} \\ T_{MG2} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} T_{ICE} \\ T_{OUT} \\ T_{MG1} \\ T_{MG2} \end{bmatrix} \tag{2}$$

2.3 Engine model

The ICE can be taken into account through its experimental furl flow map. This fuel map is the result of the adopted electronic fuel injection system's setting for regulating the air/fuel mix and is created by engineers during the construction and tests of an engine. This lookup table represents a summary of the engine’s entire operating regime with respect to torque and speed. For supervisory control studies and fast prototype design, the engine transient dynamics due to spark-timing and fuel injection are ignored.

2.4 Electric motors model

The two motor/generators assisting the thermal engine in the powertrain model are direct current machines. In our transmission model, the size and performances of the electric machines is not a design parameter, but rather an optimization parameter. This means that a model of the losses in the electric machines is not required, but rather the electric machines are already existing and manufactured. Their implementation in the transmission model goes through their correspondent loss map, which can be empirically obtained from measurement tests on the real machines. For every possible combination of torque and speed, the loss map returns the measured lost power of the electric machine.

2.5 Battery model

Based on the dynamic characteristics and working principles of the battery, the equivalent circuit model was developed by using resistors, capacitors and voltage sources to form a circuit network. In this paper we use the Rint model, which is the most popular battery model for studying hybrid powertrain design due to its capacity to simulate battery dynamics while having a simple approach. The Rint model implements an ideal voltage source V_{OC} to define the battery open-circuit voltage, together with an internal resistance R_{IN}. The variation in time of the battery State-of-Charge (SOC), $S\dot{O}C$, can thus be expressed as

$$S\dot{O}C = \frac{\sqrt{{V_{OC}}^2 - 4 \cdot R_{IN} \cdot P_{batt}} - V_{OC}}{2 \cdot R_{IN} \cdot Q_{batt}} \tag{3}$$

where P_{batt} and Q_{batt} represent the power requested from the battery and its capacity, respectively. P_{batt} can be evaluated from the power requested or provided by the MGs, adding the correspondent values of lost power from the experimental maps.

3. OPTIMIZATION-BASED HEV CONTROL

In order to assess the millions of HEV powertrain configurations above generated, a proper control strategy needs implementation. In early vehicle design phases, the powertrain operation is optimized offline. In other words, the trajectory of the vehicle speed is known a priori and it is determined by standard duty cycles (e.g. the New European Driving Cycle (NEDC), the Urban Dynamometer Driving Schedule (UDDS)). This contrasts with actual real driving conditions, where the powertrain control unit does not have input information concerning the future operating conditions. In offline HEV control, optimization-based control approaches can be adopted to estimate the fuel consumption of each analysed powertrain design and consequently identify the optimal one.

In general, three main approaches can be identified related to offline optimization of multimode power split HEVs:

1. The Pontryagin's Minimum Principle (PMP)
2. Dynamic Programming (DP)
3. The Power-weighted Efficiency Analysis for Rapid Sizing (PEARS)

All these approaches aim at analysing the HEV performance in Charge-Sustaining (CS) mode, having the battery SOC with equal values at the beginning and at the ending of the optimization time horizon.

3.1 The Pontryagin's Minimum Principle

The PMP is a general case of the Euler-Lagrange equation in the calculus of variation. It optimizes a single operating trajectory for the HEV powertrain, thus achieving local optimal solutions without guaranteeing global optimality [7]. The algorithm is dived into two steps: an inner-loop problem solved at each time point of the considered drive cycle, and a time-horizon control problem.

3.1.1 Inner-loop problem

Before solving the control problem for the overall considered drive cycle, an inner-loop optimization process is performed to obtain the family of the best ICE operating points correspondent to specific values of output torque and speed. Firstly, P_{batt} and the fuel consumption $\dot{m}_{fuel}$ are evaluated as a function of the ICE torque and speed values (T_{ICE} and ω_{ICE}, respectively) in (4).

$$P_{batt} = h(\omega_{ICE}, T_{ICE}) \tag{4}$$

The inner-loop optimal problem to minimize the fuel consumption subject to a defined battery power is then defined as

$$\min\ \left[\ \dot{m}_{fuel}\ = L\ (\omega_{ICE}, T_{ICE})\ \right] \tag{5}$$

$$\text{Subject to } \; h(\omega_{ICE}, T_{ICE}) - P_{batt} = 0$$

The optimized control variables (i.e. T_{ICE} and ω_{ICE}) can thus be defined by choosing a point of minimal fuel consumption on each feasible ICE operating line as per P_{batt}. Figure 6 illustrates all the possible operating points for the inner-loop optimization problem, discriminating between pure electric and hybrid points whether the ICE is used or not. The optimal operating points are represented in Figure 6 by the lower edge of the blue points cloud.

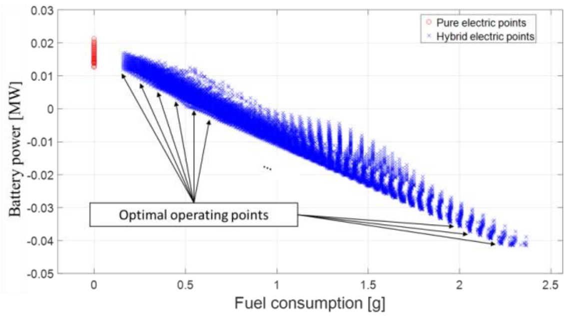

Figure 6. Instantaneous fuel consumption points for specific required output torque and speed values

In the time-horizon optimal control, this process reduces the bi-dimensional control variable (T_{ICE} and ω_{ICE}) to the single dimension ofP_{batt} only. The fuel consumption rate $\dot{m}_{fuel}$ can thus be determined fromP_{batt}, which could be decided by an on-board supervisory algorithm. The optimal ICE operating points in Figure 6 can be interpreted as a sort of Pareto frontier with a clear physical interpretation: in the best operating conditions, less battery power is needed when more fuel is consumed and viceversa.

3.1.2 Time-horizon control problem

From the assistance of the inner-loop optimal solutions, only is the control variable that decides all the operating points in the time-horizon plane of the optimal control problem. This variable sets the fuel consumption rate and the ICE operating point, which subsequently fixes all the other system variables such as the speed and torque of the MGs and the transmission status. The time-horizon control problem can thus be defined as

$$\min \; J = \int_{t\_0}^{t\_end} g(P_{batt}, t)\, dt$$

$$\text{Subject to} \quad S\dot{O}C = \mathrm{f}(\mathrm{SOC}, P_{batt}) \tag{6}$$

$$SOC(t_0) = SOC(t_{end})$$

where g is the best fuel consumption rate according to Figure 6. The optimal control variable in the PMP is obtained minimizing a performance measure, which is defined as a Hamiltonian H. Its mathematical formulation is illustrated in (7)

$$\mathrm{H} = \mathrm{g}(P_{batt}, t) + \lambda \cdot S\dot{O}C \tag{7}$$

where λ is a constant co-state variable that can be tuned to achieve the optimal control objective. Recent studies illustrated different methods to properly tune this parameter, obtaining fuel economy results consistently comparable with the global optimum [7, 8]. However, accuracy may be questionable when the operating conditions change. Moreover, tuning the equivalence factor may result computationally inefficient when dealing with component sizing in the HEV powertrain design procedure.

3.2 Dynamic Programming

The DP approach is by far the currently most applied approach for HEV control. The concept of DP was proposed by Richard Bellman in the 1940s and refined by Bellman himself in 1954 [9]. This global optimization method was firstly introduced to the HEV problem by H. Mosbech in the 1980s [10]. However, because it was constrained by the computation power available at that time, this approach did not draw much attention until the later work by Brahma et al. in 2000 [11]. Since then, this topic has been studied extensively and was extended to power-split HEVs by Liu in 2006 [12]. The DP approach guarantees global optimality through an exhaustive search of all control and state grids. Its process is implemented backward from the final drive cycle time point to the initial one by searching for the optimal trajectory among the discretized grid points, as illustrated in Figure 7. Particularly, the Bellman's principle of optimality states that the optimal policy can be obtained if a single-stage sub-problem involving only the last stage is solved first, then the sub-problem involving the last two stages, last three stages, etc. until the entire problem is solved step by step.

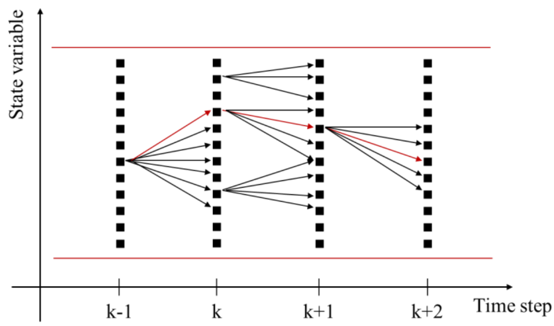

Figure 7. Dynamic programming process

For the HEV control problem, this signifies the minimization of the cost function J defined in equation (8) over the considered time horizon.

$$J = \sum_{k=0}^{N-1} \left(\dot{m}_{fuel_k} + \alpha \cdot \Delta SOC^2 \right)$$
$$\Delta SOC = \begin{cases} SOC_k - SOC_{target} & SOC_k < SOC_{target} \\ 0 & SOC_k \geq SOC_{target} \end{cases} \tag{8}$$

SOC_{target} is the desired value of battery SOC, while α represents an operating factor. DP is demonstrated to achieve global optimality under a wide range of operating conditions, but its major drawback refers to the computational power needed for exhaustively searching through all the possible solutions and tuning α.

3.3 Power-weighted Efficiency Analysis for Rapid Sizing

The Power-weighted Efficiency Analysis for Rapid Sizing (PEARS) has been introduced by Zhang et al. as a rapid near-optimal control strategy for HEVs [13]. In the PEARS algorithm, mode overall efficiency values are retained as the weighting factor for selecting hybrid or electric powertrain operation. Beforehand, speed and torque of power components are swept to determine the optimal combination in terms of mode efficiency at each driving cycle point. The overall mode efficiency values to maximize (η_{EV} and η_{HEV}) are illustrated in (9) for pure electric and hybrid modes, respectively.

$$\eta_{EV} = 1 - \frac{P_{EV}^{loss}}{P_{EV}^{in}}$$

$$\eta_{HEV} = \frac{P_{ICE\_1}\eta_G\eta_{batt}/(\eta_{ICE\_max}\eta_{G\_max})}{P_{fuel} + \mu P_{batt}} + \frac{P_{ICE\_2}\eta_G\eta_M/(\eta_{ICE\_max}\eta_{G\_max}\eta_{M\_max})}{P_{fuel} + \mu P_{batt}} + \frac{\frac{P_{ICE\_3}}{\eta_{ICE\_max}} + \mu P_{batt}\eta_{batt}\eta_M/\eta_{M\_max}}{P_{fuel} + \mu P_{batt}} \quad (9)$$

For the electric modes, P_{EV}^{loss} includes both battery loss and electric drive loss, and P_{EV}^{in} refers to the power flowing into the system. For the hybrid modes, all the possible power flows are illustrated in Figure 8. P_{ICE_1} is the engine power from the engine through the generator to the battery, P_{ICE_2} is the engine power that flow from the engine through the generator to the motor, $P_{ICE_3}$is the engine power that flows directly to the final drive. $P_{ICE\_1} + P_{ICE\_3} + P_{ICE\_3}$ is the total engine power, P_{batt} is the battery power and μ is a flag for battery assist. P_{fuel} is the rate of fuel energy injected; subscripts G and M refer to generator (when the power is negative) and motor (when the power is positive or zero). η_{ICE_max}, η_{G_max}, and η_{M_max} are the highest efficiency of the engine, the generator, and the motor, respectively.

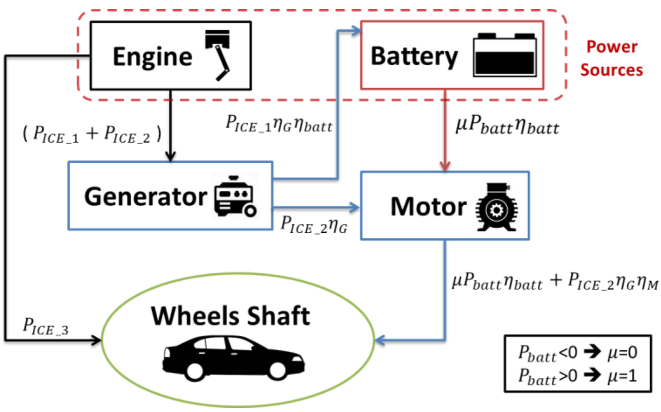

Figure 8. Power flow in the hybrid modes

Once the entire driving cycle is analyzed to extract the optimal power split for each operating mode at each time step, the powertrain is initially set to operate in electric modes only (the most efficient one according to speed and torque output). Subsequently, a recursive process starts that aims at replacing electric with hybrid operation in the driving cycle points where the smallest ranges between hybrid and electric mode efficiencies are observed. This iterative procedure is conducted until charge-balance is realized and the battery State-of-Charge (SoC) exhibits equal values at the beginning and at the end of the driving cycle. The mode-shifting schedule and the resulting fuel consumption can be evaluated in this way. Details regarding the operation of the algorithm can be found in [14].

The PEARS algorithm was demonstrated to be able to obtain results similar to Dynamic Programming (DP), while being over 10000 times faster [15] The issue with implementing a PEARS technique is that it generates an unrealistic mode-shifting schedule. To overcome this drawback, the authors of the algorithm tried to combine PEARS with DP: more uniform mode-shifting schedules were obtained, however computational cost was increased at the same time [14]. Anselma et al. [14] detected and analyzed the problematic points of the PEARS algorithm. Subsequently, a solution to minimize mode-shifting events was proposed without excessive increase of the computational cost.

4. CASE STUDY

After having presented the majorly employed optimization-based controllers for HEVs, this session presents a case study to assess the advantages and drawbacks of each control strategy. The analysed vehicle data are reported in Table 1, while the powertrain layout corresponds to the one of Figure 3.

Table 1. Vehicle parameters

Component	Parameters
Engine	188 kW @ 5800 rpm 320 Nm @ 4400 rpm
$P_{MG1_{max}}$ [kW]	60
$P_{MG2_{max}}$ [kW]	85
Final Drive Ratio	3.59
$R_1 : S_1$	3.15
$R_2 : S_2$	1.59
Vehicle Mass [kg]	2248

All the three control strategies presented above were implemented and simulated in MATLAB© software. In general, a quasi-static approach was adopted considering the time step equal to 1 second. The UDDS driving cycle profile was retained as a good representative of the urban driving conditions. The correspondently obtained results for the fuel consumption trends and battery SOC trajectories can be seen in Figure 9. Table 2 reports the calculated total fuel consumption values and the correspondent computational time considering a desktop computer with Intel Core i7-8700 (3.2 GHz) and 32 GB of RAM.

Table 2. Simulation results

Control strategy	UDDS fuel consumption [g]	Computational time [minutes]
DP	258	5
PMP	261	4
PEARS	284	2

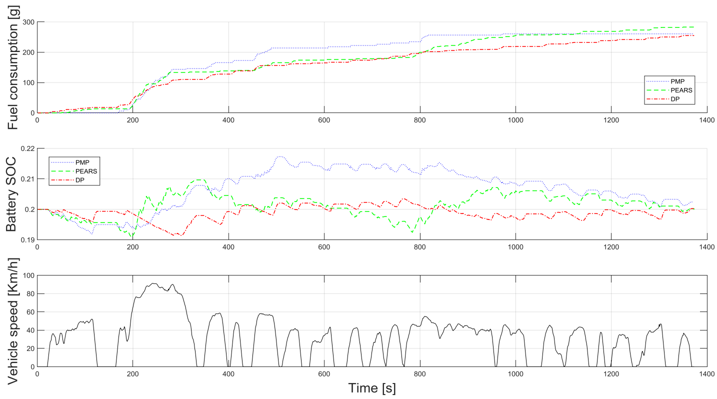

Figure 9. Simulation results for the control strategies in UDDS

Simulation results confirm the capability of reaching global optimal fuel economy employing a DP approach. On the other hand, PMP and PEARS establish themselves as near-optimal control strategies for HEVs, with the correspondent fuel economy predicted values increased by 1.16 % and 11.1% respectively. In this particular case study, the performance achieved by the PEARS algorithm in fuel economy is lightly lower than its major competitors. This is due to the PEARS especially designed for HEV powertrains with several operating modes, where it is able to realize consistent fuel economy with DP [15].On the other hand, the HEV powertrain considered in [17]*Error! Reference source not found.* can operate only one electric mode and one hybrid mode, thus compromising the flexibility and freedom to operate of PEARS. However, the PEARS achieves interesting results in terms of computational efficiency being the most rapid control strategy to determine the powertrain operating schedule. Indeed, DP requires consistently increased computational effort to evaluate the global optimal solution for the HEV control problem, while PMP represents a trade-off between the other two approaches in this sense.

5. CONCLUSIONS

In this paper, references are provided concerning the different powertrain architectures for HEVs. A modelling and optimization technique for power split HEV powertrains is illustrated, which include analytical formulations for the transmission and experimental tables for the power components.

The three mainly adopted optimization-based control techniques for HEVs (i.e. PMP, DP and PEARS) are subsequently presented and their mathematical formulations are analysed. These strategies are then simulated considering the operation of a HEV powertrain design from the industrial state-of-art in the urban driving cycle. Results show that the DP is effectively capable of achieving global optimal performance in terms of fuel economy. On their behalf, PMP and PEARS demonstrate near-optimal fuel economy results while increasing the computational efficiency. The control strategy to adopt in the HEV design process depends on the peculiar application. The PEARS algorithm reveals particularly efficient for optimizing power split HEVs with multiple operating modes, due to its ease of implementation and flexibility in the operation. Moreover, its computational rapidness represents a consistent advantage when analysing millions of different HEV powertrain configurations. On the other hand, employment of DP and PMP may be suggested for the cases of HEV powertrains with a limited number of different operating modes, since they can efficiently predict optimal fuel economy values. The optimization of a HEV architecture may demonstrate significantly improved when the accuracy of the vehicle model is increased. As an example, micro and macro road profiles may replace the standard driving cycles to simulate real-world driving conditions [15]. Moreover, including the position and the characteristics of the powertrain may be accounted as well to reduce the negative effects of vibrations [16]. Finally, the optimization reliability can be consistently enhanced when the physical perception and the behaviour of the driver are included in the model [17, 18].

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