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Analysis of Different Energy Management Strategies for Complex Hybrid Electric Vehicles

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ABSTRACT

The performance of Hybrid Electric Vehicles (HEVs) is strongly affected by their powertrain control strategies, in particular when complex architectures are concerned. Therefore the purpose of this paper is to analyze, through numerical simulation, different methodologies to develop an energy management strategy aiming to minimize the overall CO_2 emissions of the vehicle. In order to perform a comprehensive comparison, different optimization algorithms were selected among the available solutions in the control theory. Foremost a global optimization strategy, the Dynamic Programming (DP), was used to benchmark the performance of the energy management systems. Then a local optimization strategy, the Equivalent Consumption Minimization Strategy (ECMS), was evaluated, to prove its suboptimal performance and to evaluate the possibility to be implemented on a real Engine Control Unit (ECU). Finally, the potential of heuristic control techniques was evaluated due to their low computational requirements and since they represent the most common solution in real applications. The analysis focused on the case study architecture of the Chevrolet Volt, for which a Simulink model was built and tested on both regulatory driving cycles and real world driving conditions, emphasizing pro and cons of each method.

Keywords: hybrid electric vehicle, control strategies, Matlab/Simulink.

1. INTRODUCTION

Thanks to the exponential grow of computational power, ground transportation industry has accepted the reality that fast, efficient, reliable and cost effective powertrain and vehicle development necessitates the use of numerical simulation at every stage of the design process.

In particular, Hybrid Electric Vehicles (HEVs) are nowadays widely investigated as effective ways to improve the efficiency of the powertrain and thus to reduce vehicular CO_2 emissions, but their potential can be fully exploited only through the careful development of proper Energy Management Systems (EMS), capable of achieving an optimal partition between the different power sources available on board of the vehicle.

Computer Aided Engineering (CAE) techniques play therefore a fundamental role in the selection, design and development of energy management strategies of HEVs, especially for complex hybrid architectures: different approaches will therefore be analyzed in this paper through numerical simulation, aiming to develop an energy management strategy capable of minimizing the overall CO_2 emissions of a complex HEV.

2. ENERGY MANAGEMENT STRATEGIES FOR HEVS OVERVIEW

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. This implies that, at each instant of time, the power needed by the vehicle can be provided by either one of these energy sources, or by a combination of the

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two. While in a conventional vehicle the driver decides the instantaneous power delivery through brake and accelerator pedals, and his requests are translated into actions by low-level controllers, in a hybrid vehicle, since there are more power sources available, it is necessary to introduce an additional layer, the energy management system, which decides the power split between the different actuators (typically between the Internal Combustion Engine - ICE and the Electric Motors).

The choice from among all the available power-split combinations depends on the actual objective of the hybridization (i.e. minimization of the fuel consumption), which can usually be defined as the minimization of a given cost function. This process represents a typical optimal control problem that can usually be addressed through several methodologies which can differ in performance, computational requirements and computational efforts [9,14].

Generally, hybrid powertrain control strategies can be classified into the following three categories [13]:

- **Global optimization strategies,** (with full a-priori knowledge), in which the dynamic nature of the system is considered for optimization and an optimal solution is found over a predefined driving cycle, which must be known a-priori. For this reason, and for the high computational effort requested, these strategies can only be used for benchmarking, and to gain insights for the development of simpler and implementable strategies, as in the present work [2].
- **Local optimization strategies**, in which the problem of the energy management optimization is translated into the instantaneous minimization of a pre-defined cost function, taking into account both the engine fuel consumption and the use of the electrical energy stored into the battery.
- **Heuristic strategies**, which are based on a set of rules, aiming to keep the internal combustion engine operating conditions within the region with highest efficiencies. These are the most common strategies since thanks to their low computational requirements they can be easily implemented in an Engine Control Unit (ECU).

In the present study, a representative strategy was selected among each of these categories to develop a powertrain controller targeted towards the overall CO_2 emissions minimization of a complex HEV. Among the global optimization strategies the Dynamic Programming (DP) was selected to assess the ideal performance of the tested vehicle while the Equivalent Consumption Minimization Strategy (ECMS) and the Rule Based (RB) approach were selected as the most promising techniques among the other two categories. The controller performance was then evaluated on a virtual test bench, Matlab/Simulink based, able to reproduce the vehicle behavior, which was provided by the coordinators of the HEV Control Benchmark competition of the 2012 IFAC Workshop on Engine and Powertrain Control Simulation and Modeling [8].

The three selected energy management strategies will be briefly introduced and discussed in the following paragraphs.

2.1. Dynamic Programming

Dynamic Programming generates a numerical solution for an optimal control problem and it gives sufficient conditions for the global optimality [2]. DP is based on Bellman's principle of optimality and it is capable of determining the optimal solution to the discretized problem. The need for a backward procedure means that the solution can be obtained only off-line, for a driving cycle known a-priori, and therefore it is not possible to use DP for an online implementable solution; furthermore, the high computational load makes any DP optimization prohibitive on typical onboard control unit.

Nevertheless it can be used to evaluate the upper limit of the fuel economy potential of a hybrid vehicle and extract rules for real-time controllers.

2.2. Equivalent Consumption Minimization Strategy

In the ECMS the global optimization problem is reduced to a local optimization problem, solved at each instant [11]. This strategy is based on the concept that in a hybrid vehicle the usage of the electric power can be associated with an equivalent fuel consumption: the equivalent future fuel consumption (which will be needed to recharge the battery, whenever the electric power is used for vehicle propulsion) can be summed to the present real fuel consumption to obtain the instantaneous equivalent fuel consumption:

$$\dot{m}_{eqv} = \dot{m}_f + \dot{m}_{batt} = \dot{m}_f + s \bullet \frac{P_{batt}}{LHV} \tag{1}$$

where $\dot{m}_f$ is the engine instantaneous fuel consumption (fuel mass flow rate), LHV is the fuel lower heating value (energy content per unit of mass), $\dot{m}_{batt}$ is the virtual fuel consumption associated with the use of the electrical rechargeable energy storage system, P_{batt} the power delivered by the electric actuator(s), s is an equivalence factor. This latter parameter is representative of the future efficiency of the battery recharge, i.e. it translates into an equivalent fuel consumption the usage of the electrical energy stored into the battery. As a result, also the ECMS implicitly relies on some information about future driving conditions in order to tune the equivalence factor and fully exploit hybridization potential.

2.3. Rule-based Strategy

It relies on sets of empirical rules (i.e. thresholds) defined analyzing the performance maps of the engine and it chooses the power split among the energy sources by observing the operating conditions of the vehicle. This approach is computationally efficient and suitable for an on board CPU, although it usually generates results quite far from the optimality. Its calibration, in addition, could be quite difficult and it strongly depends on the driving conditions.

3. CASE STUDY DESCRIPTION

3.1. Case Study Vehicle

The Chevrolet Volt was selected as the case study vehicle, because of its sophisticated powertrain which makes the Volt a plug-in complex hybrid vehicle, and therefore an extremely challenging test case for the development of energy management strategies. The architecture powering the Chevrolet Volt consists in a power-split, planetary-based system, named Voltec and shown in Fig. 1.

Three clutches (C1, C2, C3) allow connecting or disconnecting the Internal Combustion Engine, the generator (GEN) and the main traction machine or motor (MOT).

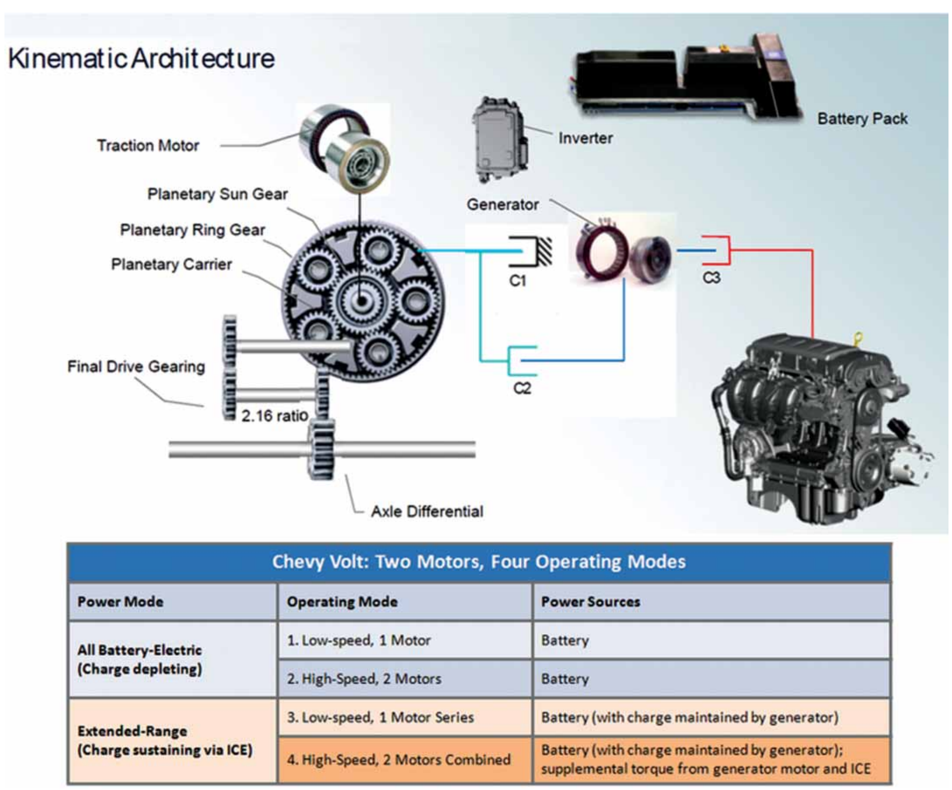
The powertrain can operate in the following modes [5,6,12]:

(1) *One-motor EV - Mode 1* (C1 locked, C2 open, C3 open, engine off). MOT alone propels the vehicle, powered by the battery.
(2) *Two-motor EV - Mode 2* (C1 open, C2 locked, C3 open, engine off). In this case, GEN acts on the planetary ring through C2, thus changing the gear ratio between MOT and the powertrain output.
(3) *Range-extender mode - Mode 3* (C1 locked, C2 open, C3 locked, engine on). This is a traditional series-HEV mode: the engine and generator are connected and produce electric power; MOT alone propels the wheels.
(4) *Power-split mode - Mode 4* (C1 open, C2 locked, C3 locked, engine on). In this mode, the three machines are all connected together with a variable speed ratio that depends on the generator speed. This mode allows transmitting mechanical power directly from the engine to the wheels, thus resulting in an overall higher efficiency than a pure series mode.

The main features of the powertrain are summarized in Table 1.

3.2. Vehicle Modeling Approach

In order to assess the performance of the different controllers, multiple modeling approaches can



Chevy Volt: Two Motors, Four Operating Modes		
Power Mode	**Operating Mode**	**Power Sources**
All Battery-Electric (Charge depleting)	1. Low-speed, 1 Motor	Battery
	2. High-Speed, 2 Motors	Battery
Extended-Range (Charge sustaining via ICE)	3. Low-speed, 1 Motor Series	Battery (with charge maintained by generator)
	4. High-Speed, 2 Motors Combined	Battery (with charge maintained by generator); supplemental torque from generator motor and ICE

Fig. 1: Powertrain architecture of the Chevrolet Volt.

ICE	
Engine Type	S.I.
Displacement	1.4 L 4 cyl.
Max Power	63 kW@5000 RPM
Max Torque	130 Nm@4000 RPM
Electric Generator Data (GEN)	
Max Power	65 kW
Max Torque	92 Nm
Max Speed	6000 RPM
Electric Motor Data (MOT)	
Max Power	118 kW
Max Torque	370 Nm
Max Speed	9500 RPM
Battery Data	
Total Energy	16 kWh

Tab. 1: Main Powertrain Characteristics

be adopted to describe the vehicle. However, a high level of detail, able to describe the dynamic behavior of each component of the powertrain [10], is not the objective of the present work. Hence, the chosen simulation model follows a "quasi-static" approach: a driver model (typically a Proportional Integral Derivative, PID) compares the target vehicle speed with the actual speed and generates a power demand profile in order to follow the target, by solving the longitudinal vehicle dynamics equation; the Internal Combustion Engine and the electric machines are described by performance maps, obtained by means of experimental measurements under steady state operating conditions. This simulation approach has been demonstrated to be appropriate for the evaluation of instantaneous fuel consumption of light-duty vehicles over the most common regulatory driving cycles [3]. In order to exploit a Matlab Function developed by the ETH of Zurich to run the DP optimization [15], a simpler model of the vehicle was also developed following a kinematic approach [10].

3.3. Tested Driving Cycles

The design of the energy management systems and the benchmark of their performance were performed in different driving conditions considering not only typical regulatory driving cycles (such as NEDC, WLTP, US06 etc.), but also real world driving conditions since the benefits achievable through the hybridization on the regulatory test procedures could significantly differ from the ones recorded in real world operations. For the sake of brevity, only the results concerning two of the real world driving cycles will be presented here below.

- **Aachen Driving Cycle.** It was recorded in the city center of the German city of Aachen, and it was chosen as representative of typical real world urban driving condition in a European city. The vehicle speed pattern depicted in Fig. 2(a) clearly shows frequent start & stop phases, quite important accelerations (with a maximum acceleration equal to 4.66 m/s^2, significantly higher than NEDC maximum acceleration, which is equal to 1.042 m/s^2) and an average speed of 42 km/h. The cycle is repeated three times, for a total 45 kilometers length, and does not show any significant altitude variation.
- **Arco-Merano Driving Cycle**. It was recorded on the Italian Alps going from the city of Arco to the city of Merano, near Trento, in Northern Italy, and it was chosen as representative of extra-urban driving conditions with significant altitude variations, with extremely demanding uphills and downhills, as shown in Fig. 2(b). This pattern, which is completely different from the common regulatory driving cycles, makes the Arco-Merano a highly challenging test case for the assessment of the energy management strategies performance, especially because of its altitude variations. This cycle shows a total length of 158 kilometers, an average speed of 52 km/h, a maximum acceleration equal to 5.66 m/s^2 and a maximum grade of 8 %.

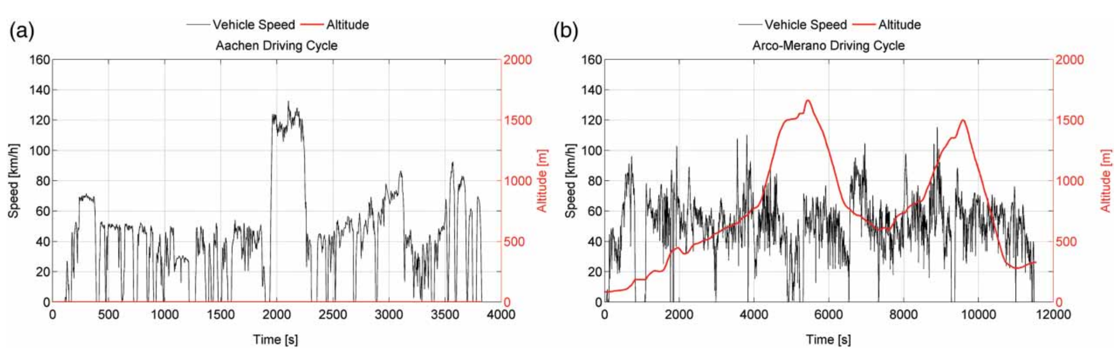


Fig. 2: Real world Driving cycles considered in the analysis – (a): Aachen driving cycle; (b): Arco-Merano driving cycle.

3.4. Optimization Target

Although Hybrid Electric Vehicles (HEVs) are mostly being developed for reducing fuel consumption, for plug-in architectures such an approach may not be suitable since it neglects the energy consumption related to the battery, which cannot be considered an energy buffer, like in a charge sustaining HEV, but is, on the contrary, an additional energy source which has to be recharged from the power grid. A possible solution to take into account both energy contributions to vehicle motion (i.e. from the fuel tank and from the battery) is to minimize the overall CO_2 emissions of the vehicle: as shown in Eq. 2, in addition to 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 has to be considered:

$$J = \frac{\mu_{CO2}}{\mu_{fuel}} \int_0^T \dot{m}_f\,(t, u\,(t))\,dt + \frac{1}{\eta_{chg} \bullet \eta_{grid}} \bullet CIE \bullet \Delta SOC \bullet E_{batt} \qquad (2)$$

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 (a value of 326 g/kWh was assumed in this work as representative of the average for the European countries belonging to the Organization for Economic Co-operation and Development (OECD) for the year 2009 [7]), 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 [1,4] 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 [16].

4. SIMULATION RESULTS

After the preliminary evaluation of the optimal performance achievable with an offline optimization through the DP, the potential of the two implementable control algorithms was verified exploiting the Simulink virtual test bench.

4.1. Benchmark Strategy: Dynamic Programming

An extensive set of DP simulations was performed in order to find the optimal driving strategy for several different driving conditions.

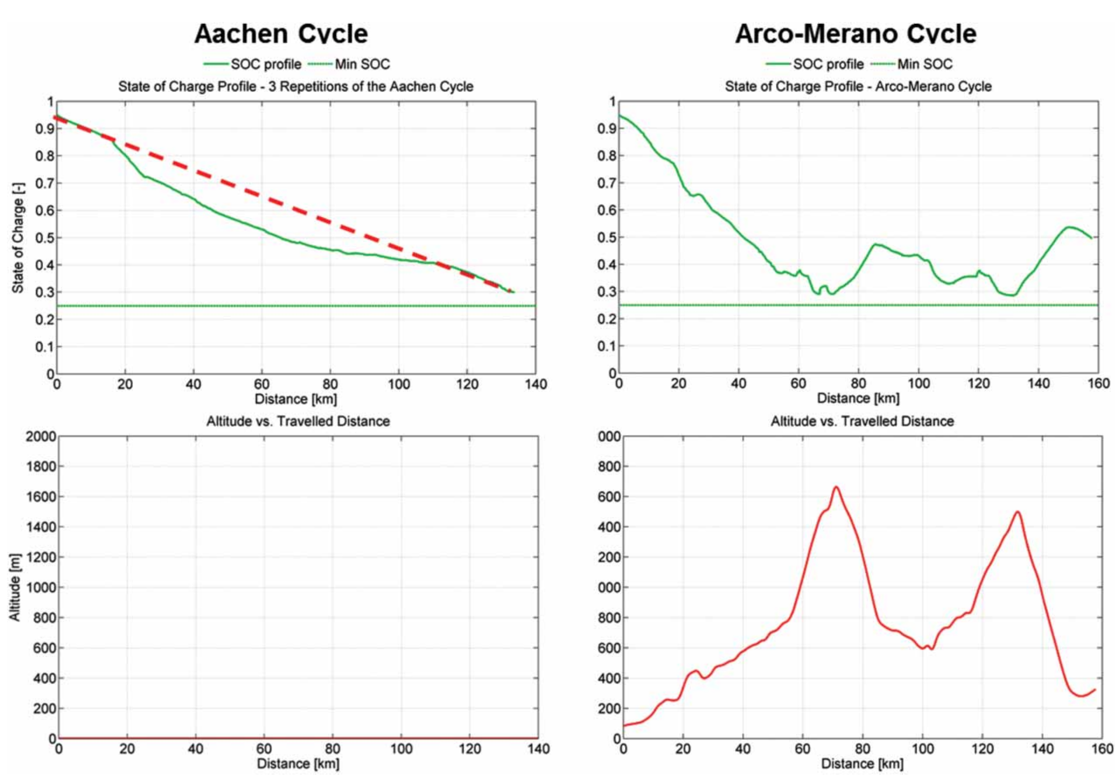


Fig. 3: DP results: SOC vs. Distance (top), Altitude vs. Distance (bottom).

Driving Cycle	Fuel Economy [l/100km]	Engine CO_2 Emissions [g/km]	Battery CO_2 Emissions [g/km]	Total CO_2 Emissions[g/km]
Arco – Merano Cycle	2.8	65	25	90
Aachen Cycle	1.8	42	40	82

Tab. 2: Fuel consumption and CO_2 emissions (DP results).

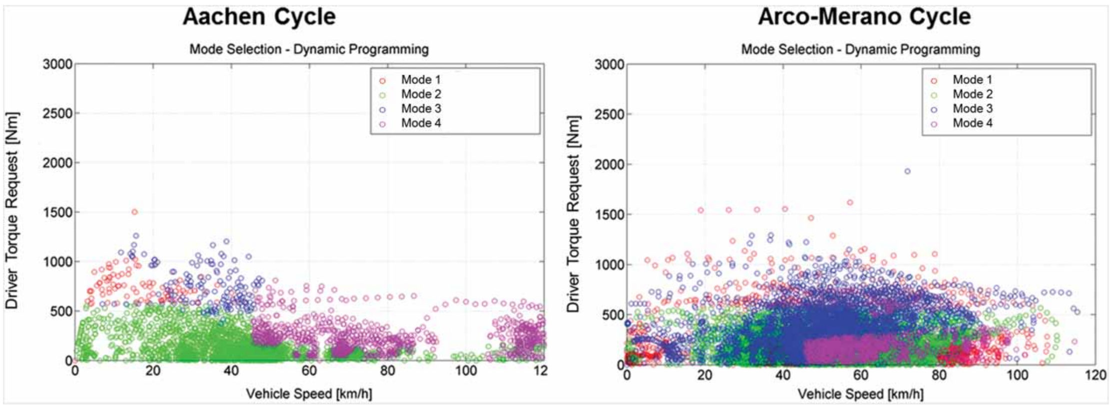


Fig. 4: Powertrain operating modes as a function of vehicle speed and traction torque request.

As shown in Fig. 3, as far as the Aachen Cycle is concerned, the DP manages the powertrain trying to achieve a linear discharge of the battery along the cycle. Since the CO_2 specific emission of the engine (about 800 [g/kWh] on average) is significantly higher in comparison with the average CIE of industrialized countries (see section 3.4), the DP exploits the battery as much as possible, trying to reach the minimum SOC at the end of the trip. On the contrary, the particular altitude pattern of the Arco-Merano cycle, with two strong downhills, leads to a SOC evolution which is no more linear with the travelled distance. In this case the DP prefers to collect all the CO_2 saving coming from the usage of the battery during the first half of the cycle (when the powertrain provides power to the wheels) and then to recover the kinematic energy of the vehicle during the downhill. Moreover it is eye-catching that at the end of the driving cycle the battery is no more fully depleted. As a matter of fact, since a strong downhill occurs just before the end of the trip, the only chance to reach the lower limit of the SOC at the end of the mission would have been to push the discharge of the battery below the lower SOC limit before the last downhill, but since the violation of the minimum SOC limit is prohibited, the best the DP can do is to reach the minimum SOC immediately before the last downhill.

The CO_2 emissions results obtained by the DP over the two driving cycles are shown in Table 2: it can be noticed that the full exploitation of the hybrid powertrain potential in terms of CO_2 emissions reduction achieved by the DP is quite impressive, since, even considering real world and highly challenging cycles, and even by taking into account the CO_2 emissions related to the battery recharge, remarkable CO_2 emissions figures, all below 90 g/km are reached.

As far as the hybrid mode selection operated by the Dynamic Programming is concerned, it can be noticed that it is strongly related to the vehicle speed and to the driver torque request, as depicted in Fig. 4, at least for the Aachen cycle, while on the Arco-Merano the Dynamic Programming strongly exploits the a-priori knowledge of the driving profile and no clear patterns can be identified in the mode selection on the basis of vehicle speed and driver demand.

4.2. Implementable Strategies

4.2.1. Rule Based

As for the DP, the rule-based strategy should aim to fully discharge the battery at the end of the driving cycle. Since no information about the future is available, this target could be approached by setting a certain trip length estimate, and then trying to achieve a linear discharge of the battery over the travelled distance, through a combination of pure EV mode and Hybrid operations. Since the powertrain of the Chevrolet Volt can operate in four modes two decision levels are required: first, the engine switch on has to be defined by means of a threshold level of the State Of Charge; then, the state of clutch 1 and clutch 2 has to be set depending on the vehicle speed.

In particular in pure electric drive the choice between mode 1 and mode 2 is based on the efficiency of the electric motor and of the generator. Because of its higher efficiency the generator (mode 2) should generally be preferred, but due to the kinematic

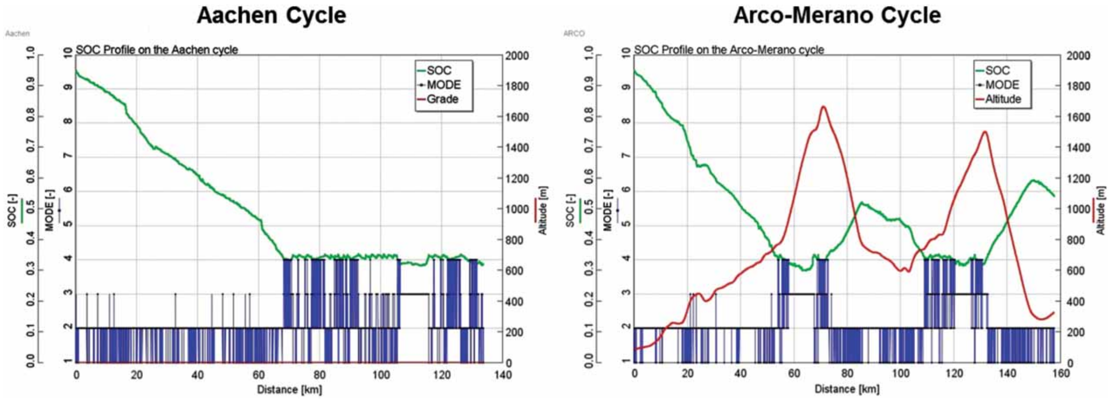


Fig. 5: RB – State Of Charge, operating mode and altitude profile as a function of distance.

relationships of the planetary gear set and to its lower maximum torque, it cannot be used to fulfill all the driver's requests.

On the other hand, the operation of the internal combustion engine in modes 3 and 4 is based on the battery SOC and vehicle speed. In mode 3 the engine will always operate at its best efficient point for each power request, while due to the mechanical coupling with the wheels, this is not possible in mode 4. So an extra rule on vehicle speed has to be implemented to ensure that the engine is kept operating at its high efficiency region.

Looking at the State Of Charge pattern shown in Fig 5, a Continuous Discharge, Continuous Charge (CD-CC) behavior can be clearly distinguished, with pure electric driving being used at the first part of the cycles, until the minimum SOC is reached after a target distance of about 70 km has been travelled. However, it can clearly be noticed that the altitude profile of the Arco-Merano cycle influences the Continuous Charge phase, because the downhill parts allow a significant regeneration of the vehicle kinetic energy, so that the operation of the engine is not needed.

In order to evaluate the computational requirements of the RB strategy, the computational time required for the simulations was estimated. In particular, on a PC equipped with an INTEL i7 3.4 GHz and 16 GBs of RAM, the simulation time for the RB control strategy was about 2000 times faster than the real time.

4.2.2. ECMS

As already mentioned in section 2.2, the equivalence factor *s* plays a fundamental role, strongly affecting the effectiveness of the ECMS. If it is too high, an excessive cost is then attributed to the use of the electrical energy and therefore the hybridization potential will not be fully exploited; if it is too low, the opposite happens and the battery will be depleted too soon. Since the optimal value of the equivalence factor is different for each driving cycle, the tuning is only possible with a-priori knowledge of the cycle. To make online implementation possible, the equivalence factor must be adapted during a driving cycle. In this work the adaptation of the equivalence factor is performed in the form of PI feedback (Proportional and Integral) on the State Of Charge, using a reference signal which decreases linearly with the travelled distance.

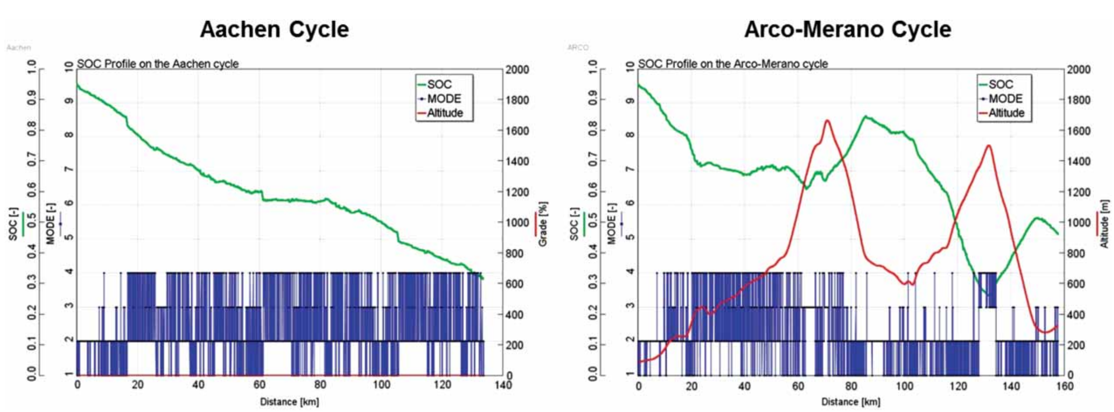


Fig. 6: ECMS – State Of Charge, operating mode and altitude profile as a function of distance.

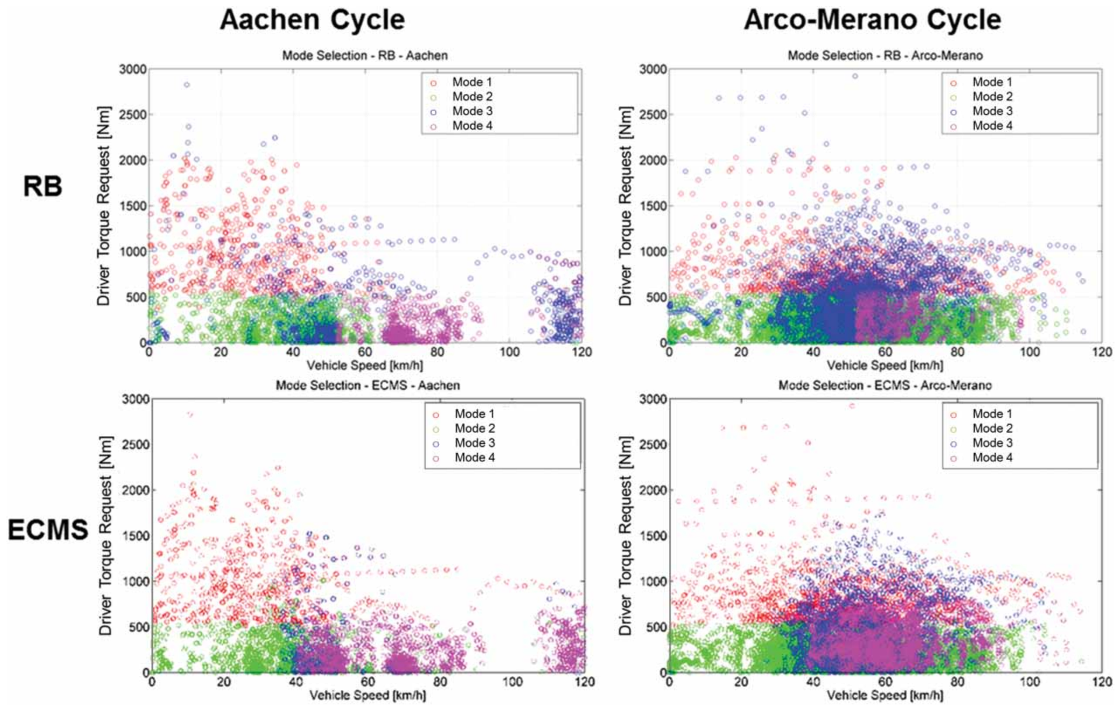


Fig. 7: RB vs. ECMS – Operating mode as a function of vehicle speed and driver torque request.

Control Strategy	Driving Cycle	Fuel Economy [l/100km]	Total CO_2 Emissions [g/km]	Δ [%]
ECMS	Arco – Merano Cycle	3.0	92	*+2%*
	Aachen Cycle	2.5	91	*+11%*
Rule Based	Arco – Merano Cycle	3.2	93	*+3%*
	Aachen Cycle	2.3	84	*+2%*
Dynamic Programming	Arco – Merano Cycle	2.8	90	[–]
	Aachen Cycle	1.8	82	[–]

Tab. 3: Fuel consumptions and CO_2 emissions for the different energy management strategies.

According to Eq. 1, the strategy determines the equivalent fuel consumption for the entire range of power splits between engine, electric motor and generator for each mode. The operating point with the lowest instantaneous equivalent fuel consumption is then selected.

As depicted in Fig. 6, while over the Aachen cycle the target of achieving a linear discharge of the battery over the travelled distance is pretty well matched, in the Arco-Merano cycle, the steep downhills in the second portion of the trip lead the ECMS to chose mainly the two electric modes for this segment, using instead the Internal Combustion Engine (enabling mode 3 and 4) in the first segment after about 20 km from the beginning.

In this case, the high volume of data which have to be processed in order to perform the local optimization strongly affects the simulation time which, however, remains still 10 time faster than Real Time.

4.2.3. RB vs. ECMS

Even though the two control strategies operate according to different principles, thus excluding the possibility of a direct comparison, few similarities can be pointed out: thanks to the kinematic constrains of the powertrain, the same hybrid modes tend to be selected depending on the torque and speed required, leading to comparable mode selection patterns, as shown in Fig. 7.

A clear transition between mode 1 and mode 2 can be noticed at a driver torque request threshold level of about 500 Nm, which is also the maximum torque that the generator can deliver to the planetary gear set. The dependence of the selection of mode 3 and mode 4 on vehicle speed is shown by the minimum vehicle speed at which mode 4 is active, which is around 55 km/h. The maximum torque of the generator also limits the operation in mode 3 and 4, so that mode 3 will be active only for low vehicle speeds and high torque demands.

As far as CO_2 emissions are concerned, although the worsening respect to the DP results was not negligible, the two tested controllers were capable of achieving performance levels comparable with the DP benchmark, without any a-priori knowledge of the mission profile. Although better results on both driving cycles were expected to be reached by the ECMS, due to its sub-optimality, the RB achieved lower CO_2 emissions on the Aahen cycle. This behavior has to be attributed to the adaptation algorithm which was chosen for the equivalence factor *s*: in order to obtain satisfactory results on different kind of driving cycles, a trade-off was chosen in the settings for the *s* factor adaptation, thus sacrificing the performance over specific cycles.

5. CONCLUSIONS

In this work a virtual test bench methodology, Simulink based, was employed to assess, through numerical simulation, the performance of different powertrain control strategies for a complex Hybrid Electric Vehicle in order to minimize its CO_2 emissions.

The design of energy management system was firstly addressed through the Dynamic Programming, in order to establish the optimal performance achievable by the vehicle.

Two implementable control strategies, a Rule Based and an Equivalent Consumption Minimization Strategy were then tested in different driving conditions and benchmarked against the DP. The main findings can be summarized as follows.

- The analysis of the Dynamic Programming results showed that a linear discharge of the battery over the travelled distance represents the optimal strategy only for vehicle missions without altitude variations.
- Both implementable powertrain control strategies achieved satisfactory results on the tested driving cycles if compared with the benchmark established by the Dynamic Programming.
- Despite the good results achieved on the tested driving cycles, the performance of the ECMS were strongly affected by the adaptation law of the equivalence factor *s*.
- Rule based control techniques were proved to be a good compromise between the achievement of optimal performance and the computational efforts.

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DEFINITIONS/ABBREVIATIONS

CAE	Computer Aided Engineering
CIE	Carbon Intensity of Electricity
DP	Dynamic Programming
ECMS	Equivalent Consumption Minimization Strategy
ECU	Engine Control Unit
ETH	Eidgenössische Technische Hochschule
EV	Electric Vehicle
GEN	Generator
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
IFAC	International Federation of Automatic Control
LHV	(Fuel) Lower Heating Value
MOT	Motor
NEDC	New European Driving Cycle
PC	Personal Computer
pHEV	plug-in Hybrid Electric Vehicle
PID	Proportional Integral Derivative
RAM	Random Access Memory
RB	Rule Based
SOC	State of Charge
US06	United States Supplemental Federal Test Procedure
WLTP	Worldwide harmonized Light duty vehicles Test Procedure