POLITECNICO DI TORINO

Master degree in Mechanical Engineering

Master’s Degree Thesis

Application of the Equivalent Consumption Minimization Strategy to the energy management of a heavy-duty Hybrid Electric Vehicle

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Contents

List of figures

List of Tables

Abstract

The present thesis aims at evaluating the performance of a real-time implementable onboard energy management strategy (EMS) for Hybrid Electric Vehicles (HEVs), namely Equivalent Consumption Minimization Strategy (ECMS). A full hybrid heavy-duty vehicle with a 4,5L compression ignition engine has been chosen as reference vehicle. A P2 parallel hybrid architecture, with the electric machine located between the engine and the gearbox, has been simulated by means of a design optimization tool developed in MATLAB programming environment. The ECMS control strategy has first been implemented in the simulation tool following a detailed Equivalence Factors (EFs) calibration, then it has been tested on different driving scenarios and finally it has been compared with the Dynamic Programming (DP) global optimizer. Also, an ICE downsizing has been advanced, to furtherly reduce fuel consumption.

Sommario

Lo scopo del seguente lavoro di tesi è di valutare le potenzialità di una strategia *real-time* di gestione del problema energetico per veicoli ibridi, la *Equivalent Consumption Minimization Strategy (ECMS)*. Il veicolo di riferimento scelto è un ibrido *heavy-duty* con un motore ad accensione spontanea da 4,5L. L'architettura ibrida che è stata simulata è P2, con la macchina elettrica situata tra il motore e il cambio di velocità, attraverso uno strumento di ottimizzazione di design sviluppato su MATLAB. La strategia *ECMS* è stata implementata sullo strumento di simulazione in MATLAB, seguito dalla calibrazione degli *Equivalence Factors (EFs)* ed è stata testata su diversi scenari di guida e confrontata con un ottimizzatore globale, la Programmazione Dinamica. Inoltre, è stata avanzata una proposta di sottodimensionamento del motore termico, in modo da ridurre ulteriormente i consumi.

1. Introduction

Regulations on pollutant emissions are stronger nowadays for the automobile industry, as persistent environmental issues and periodic energy crises are major concerns. In the last few years automobile industry has investigated different solutions to overcome the problem of reduction of fuel consumption of vehicles. In this sense, the solutions proposed regard mainly alternative powertrain technologies and advanced energy-saving vehicles.

By one hand, Hybrid Electric Vehicles (HEVs) provide promising fuel efficiency in a comparison with conventional internal combustion engine (ICE) vehicles, due to their capacity to recover energy through regenerative braking and the fact that an additional degree of freedom is available to more efficiently meet required power from the driver. On the other hand, their energy management, defined as power and torque split selection and the amount of power and torque that each source has to satisfy the driver demand, is not an easy task since is has to improve overall vehicular energy efficiency and consequently fuel consumption. Unconventional fuels vehicles have the of a lower energy content that results in a shorter driving range, compared to regular gas-powered vehicles, minimal cargo space and general lower performances taking also into account of few fueling stations nowadays [1].

It is commonly acknowledged that improvements in fuel economy of HEVs with reduced emissions is crucially dependent on their energy management strategies (EMSs). Several approaches have been proposed in literature to tackle the energy management problem, noting that the performance of EMSs is strictly related to many factors such as the actual and future velocity, the road slope, driver behavior, traffic information and state of charge of the externally rechargeable energy source. However, the complexity and uncertainty of driving conditions often compromise the performance of established EMSs. How to reduce fuel consumption of HEVs and Plug-in HEVs (PHEVs) constitutes a significant research subject for promoting shift to a more sustainable mobility.

The present thesis has the objective to describe the main PHEV control strategies, in a particular application of a hybrid truck and has the aim to prove the Equivalent Consumption Minimization Strategy (ECMS) as a reliable and easy implementable on-board algorithm that can reduce CO_2 emissions and fuel waste.

1.1 Current EU regulation for CO_2 consumption

In the frame of the interest of this work it is necessary to describe European Union regulation for CO_2 consumption. For what concerns passengers cars and Light Duty vehicles (LD), for each vehicle, a category is assigned according to a reference mass or payload and mass in running order, following the 2019/986 EU regulation [2]. The vehicles are tested according to the Worldwide harmonized Light duty Test Cycle (WLTC) obtained by the union of different driving cycles of representative countries. This cycle has substituted the New European Driving Cycle (NEDC).

Before 2012, there was an intentional agreement between European Commission and the car manufacturers, with a target CO_2 emission in the New European Driving Cycle (NEDC) of 140 g/km, to be reached by 2008 [3]. From 2009, the maximum value is variable depending linearly on the mass of the vehicle, starting from 130 g/km at a reference mass that depends on the average of sold vehicles in the last 3 years (e.g., 1372 kg in 2016). The starting value has become 95 g/km in 2020 and will decrease of 25% and 37,5% in 2025 and 2030, respectively. Each car supplier declares an average of his fleet, if this average is over the reference value, the supplier has to pay a fee-there are incentives for suppliers producing Zero or Low Emission Vehicles (ZLEV).

Regarding light duty commercial vehicles, the starting value depending on mass is 175 g/km, with the same percentage reductions in 2025 and 2030 [3].

Heavy Duty (HD) vehicles, buses and coaches are responsible for about 25% of CO_2 emissions from road transport in the EU and for some 6% of total EU emissions. Emission in heavy duty, is related not only to the fuel wastes but also to the total cost of ownership (TCO), since a vehicle consuming less fuel has a higher market value. Even if fuel efficiency is increased in last years, the increase of road traffic in the same years lead to an increase in CO_2 emission [2].

The European Regulation 2019/1242 sets CO_2 emission standards for heavy-duty vehicles, HD vehicles are tested in Worldwide Harmonized Transient Cycle (WHTC) that is a dynamometric cycle based on the Worldwide Harmonized Stationary Cycle (WHSC), with a continuous measuring of power and torque. Since the test is done directly in the engine, the limit is imposed in g/kWh.

1.2 Purpose

The purpose of the thesis is to provide and test a real-time strategy for Hybrid Electric Vehicles control, in order to reduce CO_2 emission and satisfy the request of energy of a defined driving scenario. The strategy will be implemented in a MATLAB optimization tool, that simulates a driving cycle of a hybrid powertrain governed by a defined control strategy. Firstly, an architecture of the vehicle is defined by indicating the configuration (p2, p2p4…), engine displacement, the power to energy ratio, the speed ratio of the electric machines and final drive, and the maximum charge/discharge rate of the battery. The script has as input variables the velocity of the vehicle and road slope, at each time step selects its control variables (power flow and gear number) in order to minimize a desired objective function. Whenever a control strategy is not feasible in terms of required velocity, power or energy of the battery, the control strategy is discarded and flagged as unfeasible. The output of the simulation will be the State Of Charge (SOC) level of the battery through the cycle, fuel consumption and temporal duration of the power flow.

ECMS will be simulated on a standard 4,5L p2 architecture, in different driving cycles (WHVC, FTP, JC08) and all results will be compared with Dynamic Programming (DP)-finally an ICE downsizing up to 3L will be proposed in order to furtherly reduce fuel wastes and the results will be compare with the global reduction of fuel wastes with respect to the reference pure thermal powertrain.

1.3 Outline of the thesis

This work is divided in 8 chapters:

- In Chapter 1 a presentation of context and objectives of this work is shown,
- In Chapter 2 is a brief definition of HEV and HEV architecture as well as differences with alternative propulsion systems will be proposed,
- In Chapter 3 HEVs control strategies will be shown, with a particular focus on Dynamic Programming and Pontryagin's Minimum Principle,
- In Chapter 4 a description of the vehicle model of the MATLAB optimization tool will be shown,
- In Chapter 5, Equivalent Consumption Minimization Strategy will be described deeply, alongside with calibration of EFs and results of above-mentioned tests and comparison with DP,
- In Chapter 6, a proposal of engine downsizing is advanced and results and comparison with DP are shown,
- In Chapter 7, a description of the Adaptive ECMS is shown, alongside with the different formulations,
- In Chapter 8 the entire work will be resumed, and some comments on the results obtained as well as future outlook will be proposed.

2. HEVs (Hybrid Electric Vehicles)

Hybrid Vehicles (HVs) are systems that combine two or more sources of power that can directly or indirectly provide propulsion. Hybrid electric vehicles (HEVs) represent the majority of hybrid vehicles on the road nowadays, they generally take energy from both a high-capacity energy storage (chemical fuel in liquid or gaseous form) and a lower capacity Rechargeable Energy Storage System (RESS). The RESS can be of different entities: electrochemical (batteries or supercapacitors), hydraulic/pneumatic (accumulators) or mechanical (flywheel). The energy from the two sources is then converted in power by means of a from an internal combustion engine (ICE) and an electric motor (EM) respectively, the latter is also able to recover vehicle kinetic energy to provide power assist, by means of an operative function called regenerative braking. This dual energy storage capability, in which the RESS permits bi-directional power flows, requires that at least two energy converters be present, at least one of which must also have the ability to allow for bi-directional power flows (for the former functionality mentioned). With respect to other types of conventional powertrains, HEVs guarantee a better efficiency management and add a supplemental degree of freedom to reduce fuel consumption. In this sense, HEV allow to utilize electric powertrain at low speeds and thermal at higher speeds, where they perform nearer to the optimal operating line (OOL).

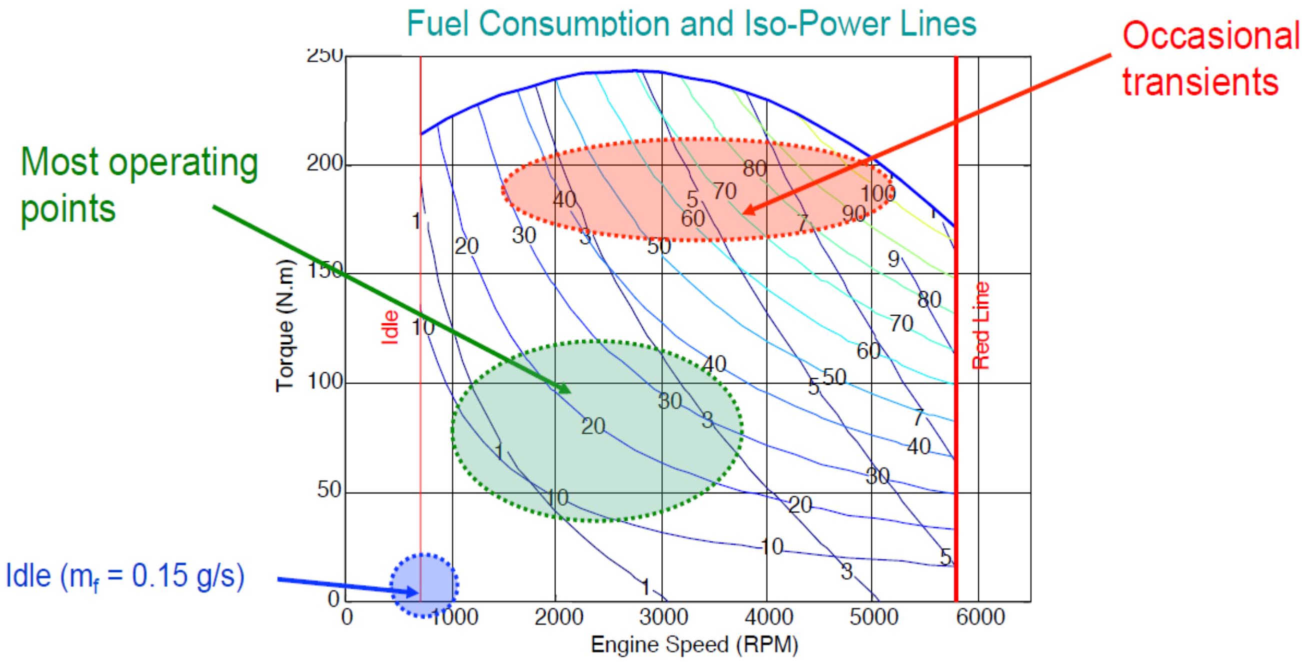

Figure 1-ICE characteristic plot [3]

As can be seen from Figure 1, conventional vehicles generally operate in the lower left quadrant of the engine operating map, to reserve power for fast accelerations and transients. This means that engines are typically oversized significantly compared to the average power required, as the engine size is determined in terms of the maximum requirements, reached only for occasional transients. Furthermore, the choices of the operating point of the engine to meet the demand at the wheel are very discrete (only a few gear ratios available to match engine speed to vehicle speed along an iso-power curve). In addition, ICE powertrains provide a less convenient fuel economy because:

- Engine fuel efficiency characteristics are mismatched with the real operation requirements: ICE is designed in terms of torque and power based on maximum vehicle speed, gradeability and acceleration,
- High dissipation of vehicle kinetic energy during braking, especially while operating in urban areas,
- Low efficiency of hydraulic transmission in current automobiles in stop-and-go driving patterns,
- Impossibility to have an optimal gear shift strategy for best performance or fuel economy as it depends on driver's behaviour. These limits can be partially overcome with AMT (Automated Manual Transmission: single or dual-clutch) or CVT (Continuous Variable Transmission) systems.

On the other hand, HEVs lead to an optimized control of the efficiencies, as they take advantage of the characteristic curve of the e-motor (EM), as the one of Figure 2:

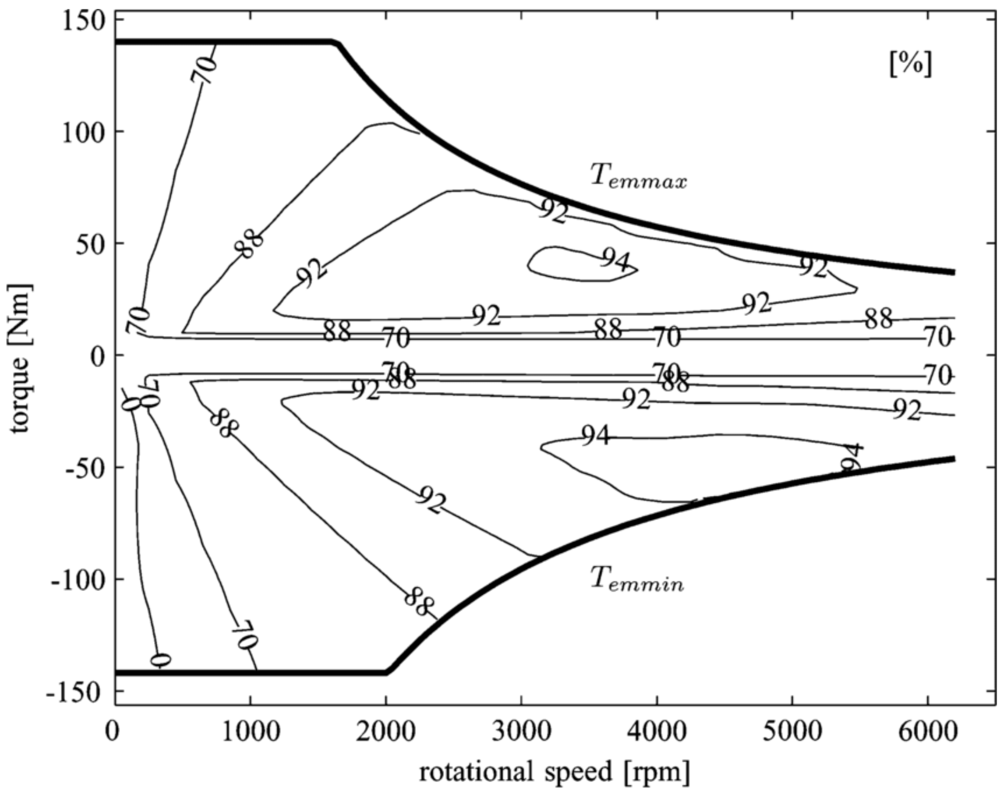

Figure 2-EM characteristic plot [4]

Furthermore, HEV can realize following functions [3]:

- Regenerative braking: when the vehicle is braking, its kinetic energy can be recovered by a generator and stored in the battery,
- Idling reduction: depending on the sizing of the secondary power source, the engine can be turned off at stops and lower speed conditions,
- ICE downsizing/downspeeding; due to the assistance of the secondary power source, a smaller ICE or a "longer" final drive can be chosen without compromising performance,
- Mitigate losses during gear shifting: HEVs are provided with automatic transmission, and losses are furtherly decreased by systems such as EVT,
- Reduce clutching losses: by not engaging the engine until the speeds are matched and do not require any slip
- Beltless engines and electric driving of accessories
- Possibility to have a more specific control over the engine operating point and engine transients: this impacts directly emissions (quasi-static and transients) as well as the drivability.

Main HEVs issues are:

- Currently more expensive than conventional vehicles,

- Heavier than conventional vehicles, due to additional weight from secondary power source and energy storage system,
- High cost of components (i.e., battery, electric machines),
- Reliability, still under study,
- More complex control systems required to optimize fuel efficiency,
- Might have drivability issues.

Nonetheless, HEVs are becoming more diffused, due to their reduced CO_2 consumption especially for urban mobility and lot of research efforts are continuously done in order to mitigate the issues listed above.

2.1 HEVs types

A first classification of HEVs can be made considering whether the batteries can be charged from an external electric source (plug-in HEVs or PHEVs) or not (non-plug-in HEVs).

Plug-in hybrid electric vehicles (P-HEVs) have the potential of further reducing fuel consumption, as well as pollutant and CO2 emissions, compared to non-plug-in HEVs but they are usually equipped with larger battery packs than non-plug-in HEVs, in order to allow a higher all-electric range (AER) to be obtained. Moreover, the incremental battery cost of plug-in HEVs might not be counterbalanced by the savings in fuel cost.

A further classification can be possibly made considering the size of the internal combustion engine (ICE) with respect to the size of the electric motor (EM) and battery.

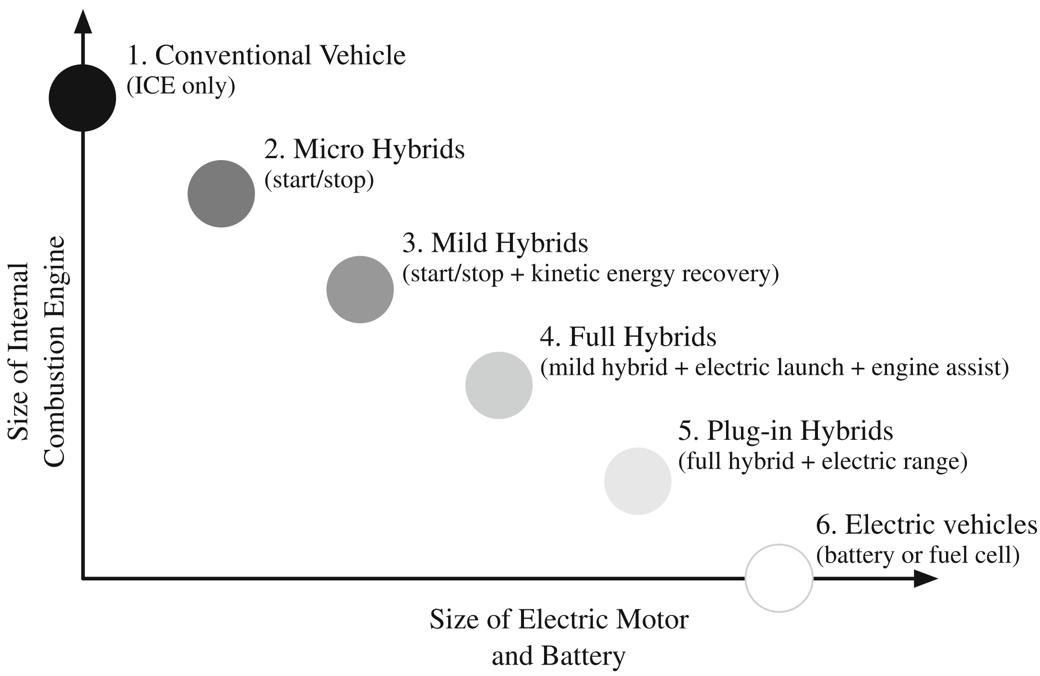

Figure 3-HEVs classification as a function of the size of the ICE and EM [4]

In Figure 3, conventional vehicle represents the less electric extreme, while pure electric vehicle represents the opposite trend. In the middle it is possible to underline intermediate solutions such as Micro Hybrids, Mild Hybrids, Full Hybrids and Plug-in Hybrids with increasing features to possibly be installed.

2.1.1 HEV series

In series HEV, electricity generated by engine motive power turns an EM to drive vehicle wheels. Power is transmitted in a straight line from a low-output ICE operated at a nearly constant speed to reduce consumption and to turn a generator, and finally operate the motor. Also, all engine motive power is converted to electricity, energy conversion efficiency turns out being low.

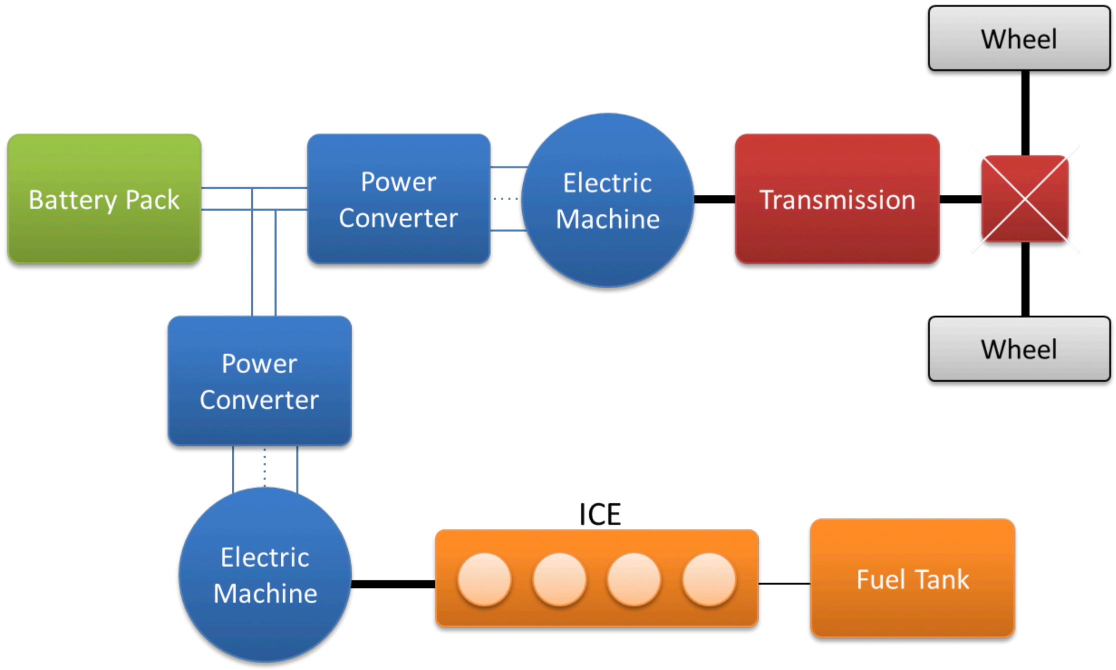

Figure 4-Series HEV scheme [3]

Degree of hybridization defines the grade of presence of the thermal power component with respect to the electrical part, in the following way:

$$R_{H_{series}} = \frac{P_{ice}}{P_{motor}} \qquad 0 \leq R_{H_{series}} \leq 1 \tag{2.1}$$

Where P_{ice} stands for the power of ICE and P_{motor} stands for the power of both electric and thermal engine. $R_{H_{series}} = 0$ corresponds to a pure electric vehicle, $R_{H_{series}} = 1$ corresponds to an electromechanical transmission.

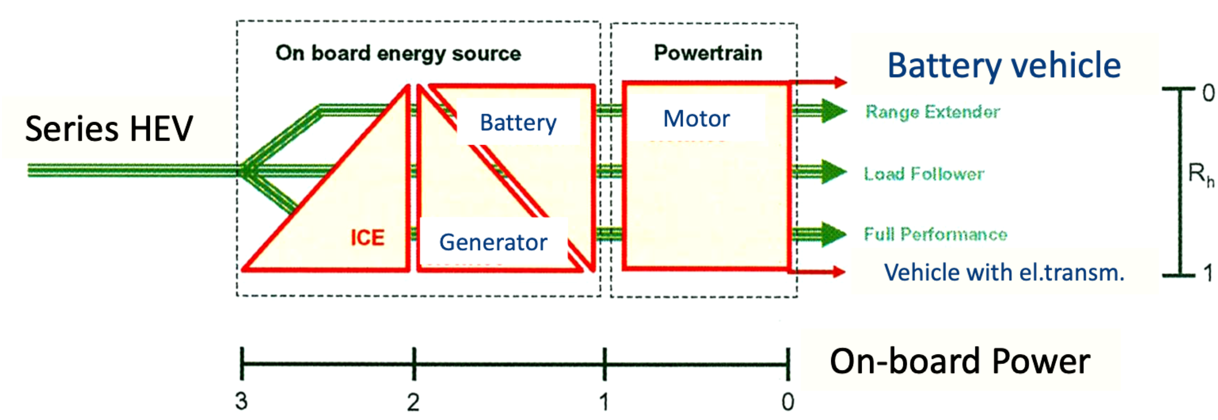

Figure 5-Degree of hybridization for series HEV [3]

Varying the degree of hybridization, it is also possible to distinguish between:

- Range Extender: featuring a low degree of hybridization, is an electric vehicle assisted by a downsized ICE that works at fixed point and high efficiency, used to power the batteries. The battery pack can be reduced based on the need to have a sufficiently long range in pure electric conditions. It has the drawback of further reducing the efficiency of the power transfer between the ICE and the wheels
- Load follower: Both ICE and generator are able to produce maximum steady-state power. The ICE follows the load time history during the cycle and during transient is assisted by the electric part. The system has higher efficiencies with respect to range extender configuration as charging/discharging cycles are reduced
- Full performance: Both ICE and generator are designed to produce maximum peak power but are not generally used for ICE applications.

2.1.2 HEV parallel

In parallel HEVs, vehicle wheels are driven by motive power from both EM and engine, power goes in parallel flows from two sources. The motor can supplement engine motive power, as well as run the vehicle while charging the battery as a generator. Motor is more compact, since it is seldom used to drive the vehicle serving a supplementary role. Motor acts also as generator, unless the generated electric power is later stored in the battery, it can’t be used to run the vehicle.

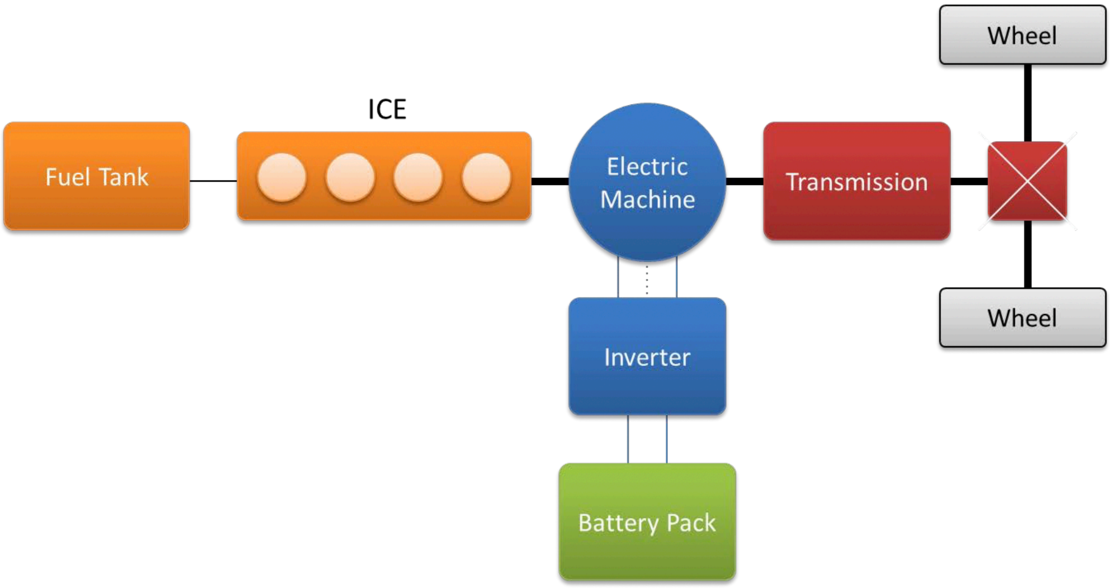

Figure 6-Parallel HEV scheme [3]

The main advantages of this kind of configuration are the fact that a generator is not necessary and loss of efficiency due to several power conversions from the engine to the driven wheels, that is now reduced. The main issue with parallel HEV is the control of the powertrain, that becomes more complex due to the mechanical coupling between the engine and the driven wheels. For the parallel HEV it is possible to derive a degree of hybridization as follows:

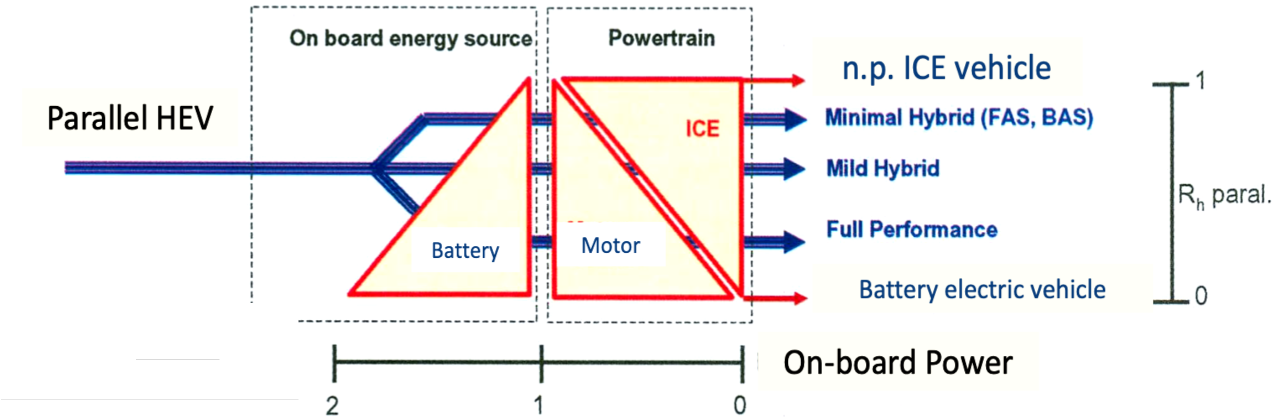

Figure 7-Degree of hybridization for parallel HEV [3]

$$R_{H_{parallel}} = \frac{P_{ice}}{P_{motor}} \quad 0 \leq R_{H_{parallel}} \leq 1 \tag{2.2}$$

$R_{H_{parallel}} = 0$ corresponds to an electric vehicle, $R_{H_{parallel}} = 1$ corresponds to an ICE powertrain.

Varying the degree of hybridization, a further distinction can be made:

- Minimal hybrid: allow the ICE to idle when the vehicle is stopped, ICE shuts down and restart to reduce the amount of time spent idling. This feature is nowadays present diffused also in conventional vehicles, which are called micro hybrids.
- Mild Hybrid: in this case ICE is coupled with an EM and the engine can be possibly turned off in some cases, when the vehicle stops. They are also able to employ regenerative breaking and some level of ICE power assist, but they are not able to provide a pure electric propulsion.
- Full performance: have the possibility to run just the ICE, just the EM or both of them. They can gain the maximum potential of hybrid, but a high-capacity battery pack is needed, for battery-only operations such as the electric start-ups. Furtherly, in full hybrid vehicles energy management strategies result to be more complex

2.1.3 HEVs series-parallel

In series-parallel hybrids, engine motive power is divided into two parts by a power split planetary gear unit. One part directly drives the vehicle wheels while the other part generates power used to supply the motor and to charge the battery. This transmission has the advantage that is capable to control generator rotational speed smoothly as a stepless gearbox with a wide speed range [5].

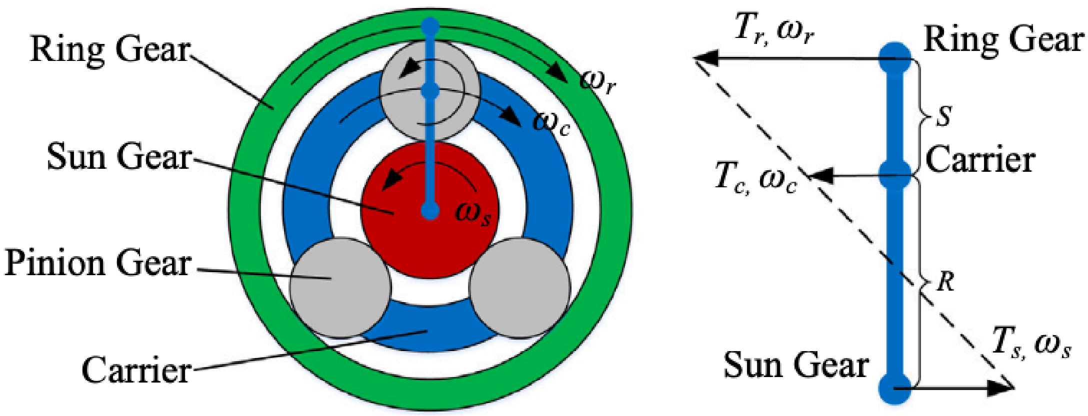

Figure 8 Planetary gear for series-parallel hybrids [5]

Mode can be switched according to driving condition between operation with only the motor or operation with both engine and motor. Has feature of both series and hybrid systems, balances fuel economy with driving performance but the system and the corresponding controls are complex and expensive. In Table 1, a resuming table with the potentialities of the different hybrid types is proposed:

Type	Fuel consumption improvement effects				Driving performance	
	Idling stop	Energy regeneration	High-efficiency drive control	Total efficiency	Acceleration performance	High output sustainability
Series	Good	Excellent	Good	Good	Moderate	Moderate
Parallel	Good	Good	Moderate	Good	Good	Moderate
Series-Parallel	Excellent	Excellent	Excellent	Excellent	God	Good

Table 1-Resuming table for HEV types

2.2 HEVs Configurations

Majority of cars on the road feature nowadays parallel HEV, which can be furtherly classified considering how the linkage between propulsion system and the wheels is made [3]:

- Double Drive (Through the road or TTR): each powertrain controls a couple of wheels, advantageous for the transmission of power but less convenient for energy management strategy and more expensive,
- Double Shaft: the linkage is in the transmission it is a shorter configuration but les common,
- Single shaft: feature a mechanical link between e-machine and thermal engine, more common

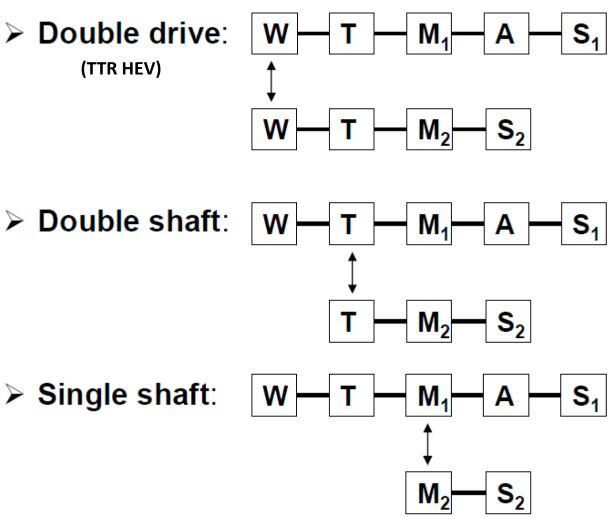

Figure 9-Classification of parallel HEVs according to linkage between the machines [3]

Within single shaft configurations it is possible to distinguish between:

- Non coaxial (Belt Alternator Starter BAS or Belt Starter Generator BSG): the ICE and the EM have different parallel axes and they are coupled by means of a belt or a chain, that represents a limit with respect to the transmissible torque,
- Coaxial (FAS flywheel alternator starter): the EM, that is an AC e-motor, is aligned with the ICE is linked with the same through a flywheel, it reduces the problem of transmissible torque but has some start-up issues.

A different classification can be possibly done according to the position of the electric motor (Figure 10):

- P1 (P1f and P1r front and rear): the EMs are directly connected to the engine. If the electric machine is located in the front side, the regenerative braking efficiency results to be low because of the energy losses between the transmission and the e-machine. P1f configuration coincides with non-coaxial configuration while P1r coincides with the coaxial configuration,
- P2: EM is installed between the engine and the transmission unit can be decoupled by means of a clutch enabling the pure electric functioning,
- P3: EM is in between the transmission and the differential unit,
- P4: EM is on the secondary axis whereas the engine is on the primary one, coincides with double drive.

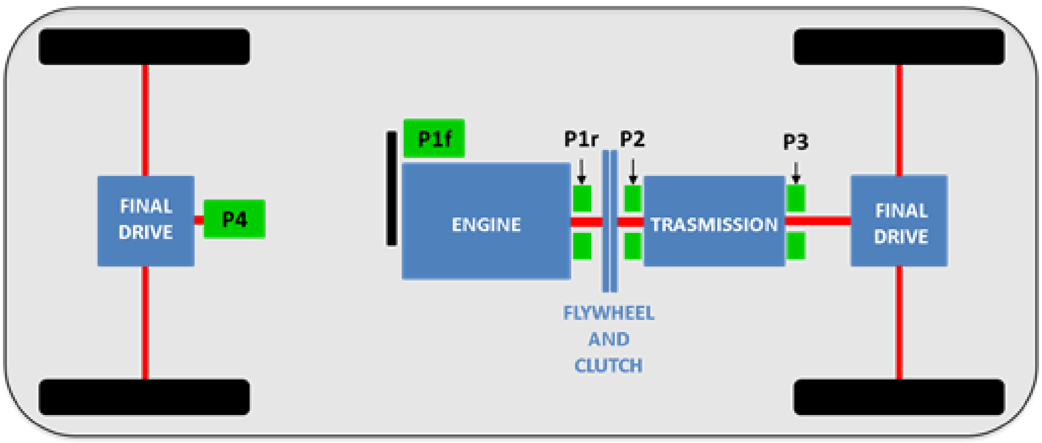

Figure 10-HEVs classification according to the position of the EM

2.3 HEVs main components

Considering the components that bring the power exploited by both the thermal and the electric engine to the wheels, a brief overview on some of them will be proposed.

A Motor-generator (MG) has the task to provide supplemental motive power for the engine and can operate independently depending on vehicle running condition. Motor assists engine output to achieve superior power performance for smooth take-off and acceleration. Also, when regenerative brake is operating, MG is able to work as a generator to convert vehicle kinetic energy into electric energy to charge the HV battery. The generator additionally serves as a starter for the engine. It is made up of different stators and rotors that include permanent magnets and resolvers (rotational angle sensor). Transmission system configurations and construction (including the motor and the generator) differ according to the vehicle manufacturer and vehicle model.

MG exploits its power by controlling the rotating magnetic field with respect to rotor rotational position and speed, permanent magnets attached to the rotor are pulled upon the magnetic field, generating torque, that is proportional with the intensity of the current. Rotational speed is controlled by the frequency of the AC and an elevated torque can be generated even at high speed by appropriately controlling the angle between rotating magnetic field and rotor magnets.

Inverter converts current from the HV battery to the three phase AC that drives the motor. In addition, inverter converts AC to DC for the battery in the HV battery: AC produced by generator via engine motive power and AC produced by the motor via regenerative braking. Inverter is made of multiple insulated gate bipolar transistors (IGBT), a semiconductor switching element capable of switching large currents at high speeds. They are able, when turned off and on to convert from direct current to three phase alternate and viceversa and change the direction and magnitude of the current.

DC-DC converter converts high voltage from battery to supply power to electrical auxiliary equipment (audio devices and light) and also has the task to charge the auxiliary battery. The DC-DC converter also converts high voltage DC from the HV battery into AC, this is stepped down into a low-voltage AC, rectified and then smoothed for output as a low voltage DC.

The energy flows is:

1) DC-AC converter: from high voltage DC to AC by operating a bank of transistors ON and OFF,

2) Transformer: Steps high voltage AC down to low-voltage AC using magnetic induction properties that cause an electromotive force to be generated in a coil when current is passed through an opposing coil,
3) Rectifier: Converts stepped down AC into DC using the characteristics of a diode that allow only current flow in one direction,
4) Smoother: Converts intermittent DC that follows rectification into a smooth DC using a condenser and a coil smoothing filter.

Boost converter raises HV battery voltage to a higher value to supply the inverter, motor output is improved by raising the high voltage value. In addition, boost converter steps down the high voltage from the inverter to charge HV battery. Uses a characteristic of reactors that stores and discharges energy to generate a voltage output higher than the voltage input.

HV battery is comprised of multiple modules connected in series. A cell is the smallest structural unit of the battery, a module is made of a several cell assemblies with different cells connected in series to create high voltage. For instance, in Toyota Prius 30, one module consists of 6 1,2-volt Nickel-Metal Hybrid (Ni-MH) cells with totally 28 modules used to generate high voltage with each module made by 6 cells. There are different battery types with voltage varying from 100 to 400 V, equipped with a manual power supply cut-off and power supply control relay to connect and disconnect high voltage circuit. Table 2 shows the main battery types:

Type	Construction	Features
Nickel-Metal Hydride (Ni-MH) Battery	Uses nickel hydroxide for the positive terminal, hydrogen storing alloy for the negative terminal, concentrated aqueous solution of potassium hydroxide for the electrolyte.	• Superior electrical discharge performance under large power/large currents, reduced danger of rupture, relatively cheaper than Lithium-Ion
Lithium-Ion (Li-Ion) Battery	Uses lithium metal oxide for the positive terminal, a carbon material such as graphite for the negative terminal, a non-aqueous material for the electrolyte	• Produces high voltages, and has a high energy density, no memory effect: phenomenon in which if battery with a sufficient amount of charge remaining is repeatedly charged, amount of usable capacity appears to decrease

Table 2-HEV HV battery types

2.4 Comparison between HEVs and Battery Electric Vehicles (BEVs)

Battery equipped electric vehicles (BEVs) have only a battery as the energy source, and traction power is provided by one or several electric machines. These vehicles are highly energy efficient and feature zero tailpipe emissions, while the well-to-wheel (wtw) emissions depend on the electric energy production process: if the electric energy is derived from a renewable source, wtw emissions can be reduced to a great extent. However, these vehicles have not a good diffusion on the market, due to higher costs, added weight of the vehicle, reduced load capacity, limited driving range and the lack of recharging infrastructures on the roads.

3. HEVs control strategies

Energy management strategies are necessary to pursue the full potential of hybrid electric vehicles and furtherly reduce fuel consumption and emissions with respect to conventional vehicles. The presence of an additional energy storage device gives rise to new variables, which in turn translate into the need of finding the most efficient way of splitting the power demand between the engine and the battery. Consequently, control strategies have to deal with various control parameters, and sometimes can require high calculation times and are not easy to implement onboard.

Controlling a HEVs is made essentially by two layers of tasks [4]: one is referred as component-level control task, where each powertrain component is controlled by using classical feedback control methods. The second one, is a supervisory control, responsible for the optimization of the energy flow of the vehicle and maintain the battery state of charge within a certain range of operation and other requirements.

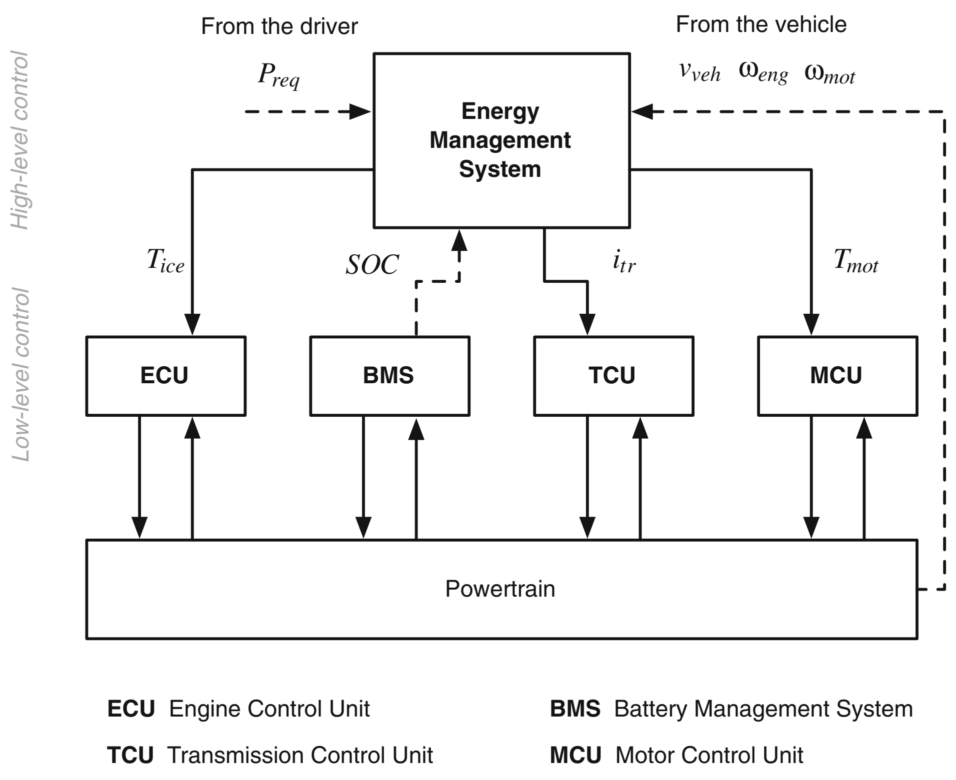

Figure 11- Energy Management system for HEVs [4]

This latter is referred as Energy Management System (EMS) that receives and processes information from the vehicle (ω_{eng}, ω_{gb}, ω_{mot}) and the driver (v_{veh}, a_{veh}, δ) to obtain the optimal set-points sent to the actuators and executed by the low-level control layer. The EMS also

selects the best modes of operations of the hybrid powertrain, including start–stop, power split, and electric launch. Essentially, controlling a HEV consist in managing, for each instant of a driving pattern, the power flows in order to achieve precise requirements of the vehicle such as torque or power needed.
This work is focused on testing an EMS that is responsible for the optimization of the power split on-board of the vehicle while maintaining the battery state of charge within a certain range of operation and reduce fuel consumption and CO_2 emissions.
In fact, it has been proven that there could be improvements in fuel economy for HEVs ranging from 10% for mild hybrids to more than 40% for full hybrid vehicles [6].

3.1 Control parameters

State of charge (SOC) is an index that expresses the HV battery charge state as a percentage, is calculated starting from values such as battery voltage, input/output current and temperature. HV battery is repeatedly discharged during acceleration while using the EM, and continually charged during deceleration via regenerative braking. The drive power and amount of power generated from motor and generator are controlled to preserve the HV battery SOC value in the optimal state even when the battery is repeatedly charged and discharged. State of Charge (% of total capacity) of electrical accumulators (batteries, supercapacitors). It could also be applied to other accumulator types used for the secondary energy storage.

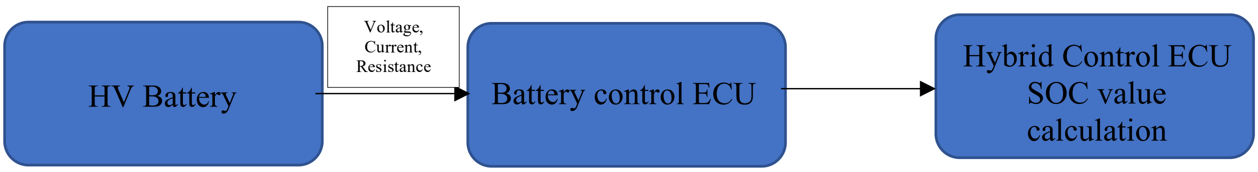

Figure 12-Scheme of the energy chain from the battery to the ECU for HEV control

Referring to SOC of the battery through the driving pattern, it is possible to distinguish between two trends:

- Charge depleting is a SOC trend that allows battery to fully discharge to its minimum admissible value through the cycle. This SOC strategy is the more prone to minimize the use of the thermal part and the fuel consumption accordingly but is only compatible with P-HEV as it is strictly necessary to recharge the battery from an external source,
- Charge sustaining is a SOC trend that allows the battery to recharge continuously during the cycle in order to maintain the SOC level as near as possible to the target or reference

value. This trend is crucial for non-plugin HEVs, so that the battery SOC level is bounded to a minimum level to allow for a pure electric take-off.

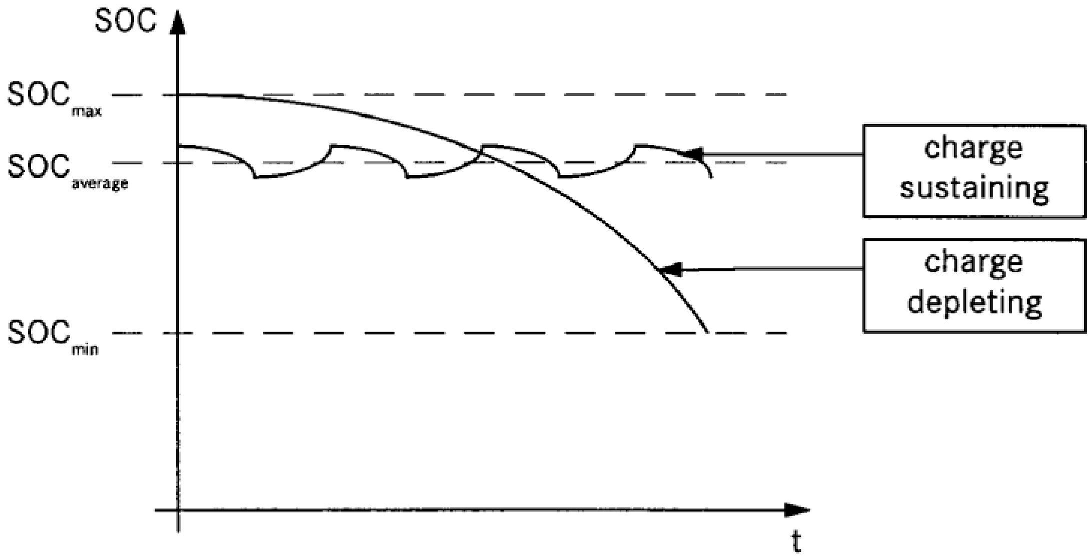

Figure 13-Comparison between charge depleting and charge sustaining behaviour [3]

A visual representation of how the trends shown affect SOC variation in time is shown in Figure 13.

As regarding the modes that the model parallel HEV can perform, a distinction may be done:

1) Pure thermal (PT): only the ICE is used for moving the vehicles, with EMs turned off,
2) Pure electric (PE): only the EM is used for torque generation and thermal engine is switched off, it also includes generative braking,
3) Power split (PS): both ICE and EMs are used to satisfy the power requirement of the driving pattern,
4) Battery charging (BC): EM acts like a generator, when there is an excess of power by the thermal engine, in order recover energy in the battery.

In the following section, main control strategies for HEVs will be shown alongside with some considerations, advantages and drawbacks of each of them.

3.2 Types of Energy Management Strategies

Firstly, it is possible to divide the state of the art of EMs in [3]:

- Global optimization methods or benchmark methods such as Dynamic Programming, genetic algorithms, Pontryagin's Minimum Principle,
- Instantaneous optimization methods such as Equivalent Consumption Minimization Strategy,

- Heuristic methods such as rule-based methods with offline maximization of components efficient or though control maps,
- Artificial intelligence-based methods such as rule-based methods based on unsupervised learning.

In this work, another proposal will be advanced by distinguishing between two types of control [4], that will be analyzed: rule-based and model-based control strategies.

3.2.1 Rule-based energy management strategies

Rule-based approaches on heuristic are based on the idea that the controlling decision is done with a precise set of rules, set a priori. In this sense, there is not the precise aim to minimize an objective function, but rule-based act with a prescribed set of information, that can be based on several factors. They can be based on a multiple decision layer scheme, in which different parameters are taken into account or either map-based decision strategies, that assign a decision in relation to two parameters. An example of the latter is shown on Figure 14:

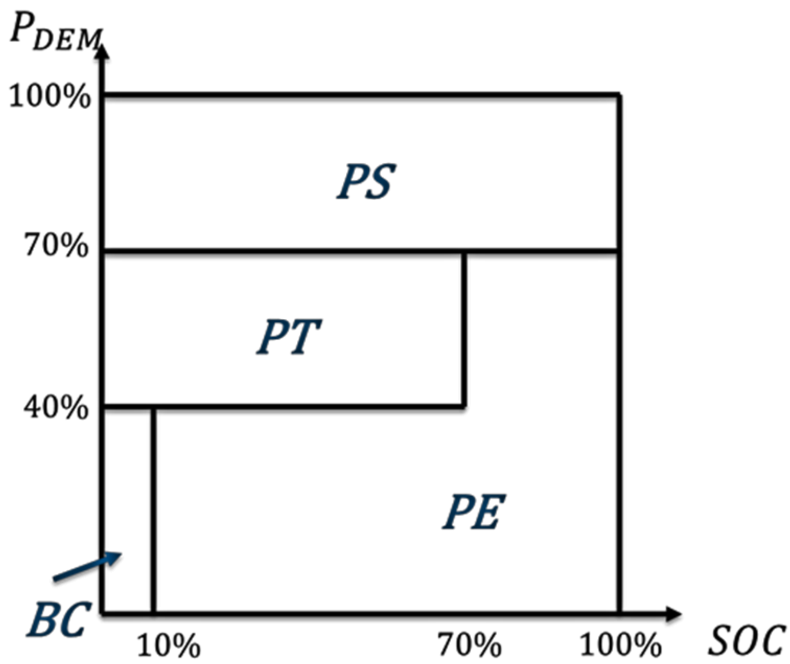

Figure 14-RBC example for a PHEV [3]

Another rule-based control is through Genetic Algorithm (GA), that mimic the natural evolution process, generating an initial population of potential solutions by generating new individuals and maintaining only the best ones. Each individual is evaluated, and a score called fitness is assigned to it according to the value assumed by the objective function J. In the control strategy optimization, the genome is constituted by the values of given control variables at each time instant of the mission (gear number and power flows).

Due to a lean structure of the algorithm, map-based control strategies offer a fast implementation for real time application, but it has several drawbacks:

- To obtain a proper map is a tedious process that needs long time,
- It is not possible to obtain a single map that is optimal for different driving cycles.

3.2.2 Model-based energy management strategies

Model-based energy management strategies are based on decision done according to the minimization of a so-called objective or cost function, in a fixed driving cycle. In fact, to minimize the objective it is necessary to know both the actual and the future driving pattern.

Model-based energy management strategies are in turn divided into numerical and analytical approaches.

Numerical optimization strategies take into account the whole driving cycle and find the optimum numerically. On the other hand, analytical approaches use a formula appliable at each instant, and make the solution faster. The first category includes methods such as simulated annealing, genetic algorithms, and dynamic programming, that will be discussed in detail. The second category comprehends Pontryagin's Minimum Principle (PMP) and Equivalent Consumption Minimization Strategy (ECMS) that will be deeply analysed, being the object of this work. Also, both DP and PMP are global control methods, due to the fact that, to be functional they need knowledge of the entire problem in advance and for this reason are generally used as benchmark for the instantaneous methods, such as ECMS, that can be implemented on-board.

3.2.2.1 Dynamic Programming

Dynamic Programming (DP) is a mathematical optimization tool developed by Richard Bellman in 1950s and counts different applications in economics and engineering fields. The idea behind DP is to face decisions dividing the problem in different stages. It has a great potential to solve complex problems on the downside that requires the whole information-in this case the driving cycle-in order to give an optimal solution. That's why DP is widely adopted as benchmark for the identification of the optimal strategy in HEVs. The algorithm is based on the *Principle of Optimality* which essentially states that from any point of an optimal trajectory the remaining trajectory is optimal for the corresponding problem initiated at that point [4]. A sequential optimization problem is defined as follows:

$$x_k = f_k(x_k, u_k)\ with\ k = 0,1, \dots, N-1 \tag{3.1}$$

u_k is the control variable whose time is chosen at time k, both u_k and k are discretized and bounded. Considering a control policy over N time steps:

$$u = \{u_0, u_1, \dots, u_{N-1}\} \tag{3.2}$$

A cost of the policy u is defined starting from initial conditions x_0:

$$J(x_0, u) = L_N(x_n) + \sum_{k=1}^{N-1} L_k(u_k, x_k) \tag{3.3}$$

Where L_k represents the instantaneous cost function. This considered, the most optimal solution is defined as the one with:

$$J^*(x_0) = \min J(x_0, u) \tag{3.4}$$

And the corresponding optimal policies are:

$$u^* = \{u_0^*, u_1^*, \dots, u_{N-1}^*\} \tag{3.5}$$

The DP computational grid also takes into account the backward process, starting from the final step N the algorithm uses the control that gives the optimal cost-to-go and considering the terminal cost Y_k:

$$u_k = \mu^*(x_k, k) = \arg\min\big(L_k(x_k, u) + Y_{k+1}(f_k(u_k, x_k), u_k)\big) \tag{3.6}$$
$$for\ k = N-1, N-2, \dots, 1$$

The optimal control sequence is consequently found by proceeding backward from the final step, choosing at each instant the control that minimizes the cost-to-go $Y_k(x_k, u_k)$, and storing in a matrix μ^* the optimal choice at each time instant k and state x_k.
The logic behind DP can be visually seen considering that the algorithm consists in finding the optimal path or *"cost-to-go"* from the initial state to the final one (e.g., path from node A to node K in Figure 15). This can be done by proceeding backward from the final state to the

initial one and saving the optimal path at each time step (i.e., each level of the grid). Once we get the optimal solution, the algorithm can proceed forward along the optimal path. The optimal, and so the objective function J can be set for different objectives (fuel consumption, NO_x reduction etc.). Also, miscellaneous objective function can be considered, for instance:

$$J = a\frac{FC}{FC_{ref}} + (1-a)\left(\frac{NO_x}{NO_{x_{ref}}}\right) \tag{3.7}$$

In this case, $a = 1$ is Fuel Consumption oriented whereas $a = 0$ is NO_x oriented.
For this application the intent is to reduce fuel and CO_2 consumption, so the objective is set as the minimum of the J function CO_2 oriented.

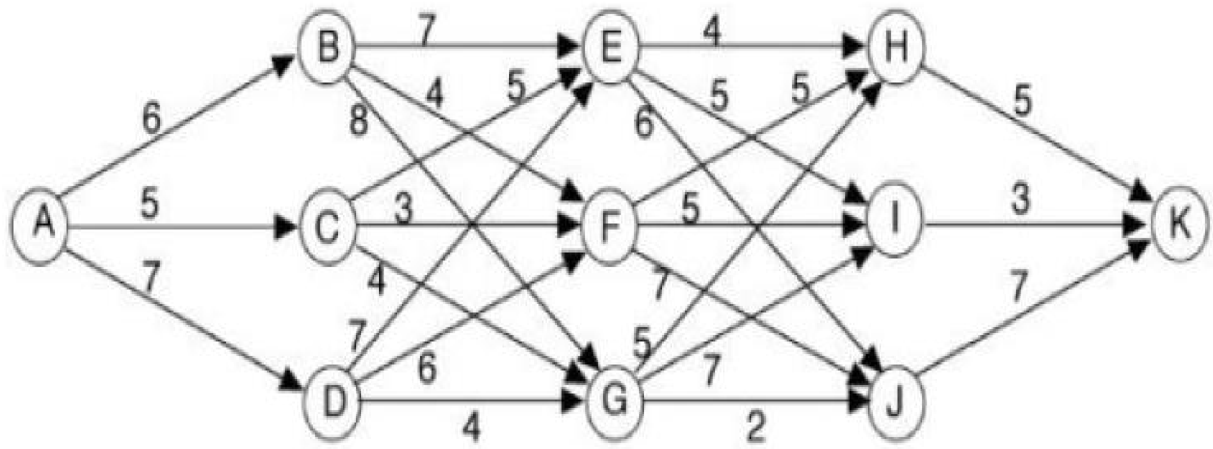

Figure 15-Dynamic Programming (DP)

Applying the DP to HEV control, the control policy u_k is the power split between the two propulsion systems whereas the cost related is to be ascribed to a precise objective function, referred to fuel consumption, CO_2 or NO_x emissions, any design objective. In the optimizing tool in MATLAB, a cost is related to the state of the powertrain and the power required. All possible power splits and the related feasibilities and costs are stored in the matrix of costs, with unfeasibility representing a control that does not give enough power for the mission or a control that exceeds the limits in SOC-unfeasible combination have an infinite cost in the matrix. For the latter reason, unfeasible strategies are automatically discarded and when the whole path is exanimated, in the backward phase, the path with lower cost represents the optimal solution.
Here in Table 3, it is possible to see some advantages and downsides of DP:

Dynamic Programming (DP)	
Advantages	**Drawbacks**
• Overall control of non-differential non-linear problems • Wide range of application • The algorithm converges at the optimal real solution	• Mission characteristics must be known a priori • Accurate discretization required • Complex definition of the computational domain • High level of programming and long time for reaching the convergence (not suitable for on-board application but as a powerful benchmark tool)

Table 3-Dynamic Programming advantages and drawbacks

As will be seen through the thesis, DP represents one of the most optimal control strategies the results obtained by this type of controller will be set as benchmark in order to prove the validity of the controller tested.

3.2.2.2 Potryagin's minimum principle (PMP)

Pontryagin's Minimum Principle (PMP) defines an optimal control law, when a set of conditions are satisfied, this condition is referred as extremal [4]. So, a set of constraints is defined and in particular application of HEVs control strategies, there are constraints both on state and control variables. The state variable SOC, for instance, has to vary between two values, SOC_{max} and SOC_{min}, and also control variables do not have to exceed the admissible points (for instance, the power of both the ICE and the EM can't go above the maximum nominal power). For the application in HEV control the Hamiltonian function is defined alongside with the power demand from the driver [4]:

$$H\left(SOC(t), P_{batt}(t), \lambda(t), P_{req}(t)\right) = \dot{m}_f\left(P_{batt}(t), P_{req}(t)\right) + \\ +\lambda(t) \cdot S\dot{O}C(t) \qquad (3.8)$$

Where λ represents the co-state variable. The optimal control is the one that minimizes the Hamiltonian function and respects different conditions:

$$P_{batt}^{*}(t) = \arg\min H\left(P_{batt}(t), SOC(t), \lambda(t), P_{req}(t)\right) \tag{3.9}$$

$$S\dot{O}C^{*}(t) = f\big(SOC^{*}(t), P_{batt}^{*}(t)\big) \tag{3.10}$$

$$\dot{\lambda}^{*}(t) = \big(-\lambda^{*}(t) + w(SOC)\big)\frac{\partial f}{\partial SOC}\big(SOC^{*}(t), P_{batt}^{*}(t)\big) =$$

$$= h(SOC^{*}(t), P_{batt}^{*}(t), \lambda^{*}(t)) \tag{3.11}$$

$$SOC^{*}(t_0) = SOC_0 \tag{3.12}$$

$$SOC^{*}\big(t_f\big) = SOC_{target} = SOC_{final} \tag{3.13}$$

$$SOC_{min} < SOC^{*}(t) < SOC_{max} \tag{3.14}$$

Condition (3.13) represents the charge sustaining behaviour that has to be guaranteed for non-externally rechargeable vehicles as the one tested in this work.

Now the problem of PMP is on how to determine the co-state variable. A solution is to determine the value by using the shooting method namely by guessing an initial value and increasing or decreasing it starting with an initial value of λ_0, at each iteration of the shooting method the minimum principle conditions are verified in a particular segment of the driving cycle. At the end of the simulation, the obtained SOC value at each segment is compared to the desired state of charge, SOC_{target}. Depending on the difference between the actual value and the target value, the value of λ_0 can be properly tuned (increased or decreased) and the simulation repeated, or the algorithm can finish when there is an acceptable difference between the reference and the actual SOC level. A bisection procedure can be used to obtain convergence in few iterations, making the minimum principle sensibly faster than dynamic programming. The calibration of co-state value λ_0 can be seen in the scheme in Figure 16:

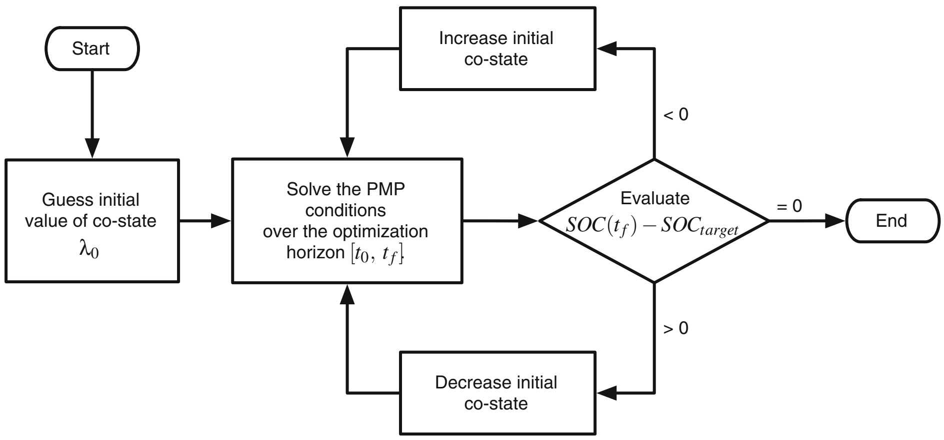

Figure 16-Scheme for co-state parameter calibration in PMP [4]

4. Vehicle model

In this section, a brief description of MATLAB optimization tool and HEVs control will be given. It will provide an overview over the model of the main components and the driving cycles. The simulation of the driving cycle is a problem discretized both in time and in space domain, with an interval grid approach. All equations, subsequently, are considered at both extremes of the node.

4.1 Input variables

Input variables of the problem are vehicle velocity v_i and the slope of the road, obtained by the driving cycle. For each time instant, the power required by the vehicle P_v is calculated by considering the contribution of the rolling resistance $P_{v,roll}$, the grade resistance $P_{v,grade}$, the aerodynamic drag resistance $P_{v,drag}$ and the inertia resistance $P_{v,inertia}$, as follows:

$$P_v = P_{v,roll} + P_{v,grade} + P_{v,drag} + P_{v,inertia} \tag{4.1}$$

In which:

$$P_{v,roll} = V_v \cdot m_v \cdot g \cdot r_v \cdot \cos \alpha_r \tag{4.2}$$

$$P_{v,grade} = m_v \cdot g \cdot V_v \cdot \sin \alpha_r \tag{4.3}$$

$$P_{v,drag} = \left(\frac{1}{2} \cdot \rho_{air} \cdot c_x \cdot A_v \cdot V_v^2\right) \cdot V_v \tag{4.4}$$

$$P_{v,inertia} = \left(m_v + \frac{I_{wh}}{R_{wh}}\right) \cdot V_v \cdot \dot{V}_v \tag{4.5}$$

In which, m_v is the mass of the vehicle, g is the acceleration of gravity, r_v is the vehicle rolling resistance coefficient, α_r the slope of the road, ρ_{air} is the density of the air, c_x is the aerodynamic drag coefficient, A_v the frontal area of the vehicle, I_{wh} is the inertia of the wheel, R_{wh} is the dynamic radius of the wheel. The total power is used to calculate the power required for each component (front and rear axle, final drive) and finally to the ICE and the EM. For the ICE, the EM and the battery, a map is created using a scaling factor, obtained considering the reference map provided by the manufacturer. Each component is analyzed in order to verify if it is capable or not to supply power and velocity requirements by looking at the previously generated maps, when the power required is higher than the maximum one, an unfeasibility flag is set.

4.2 Control and state variables

In the MATLAB optimization tool, the control variables are the gear number and the power flows. As stated in chapter 3, there exists 4 types of power flows in a Parallel HEV and consequently the control variable related to power flow N_{PF} varies from 1 to 4, with: $N_{PE} = 1$ $N_{PT} = 2$ $N_{PS} = 3$ $N_{BC} = 4$. In addition, since the vehicle is equipped with a 6 gears transmission gearbox the control variable related to gear number N_{GN} varies from 1 to 6. Considering that the engine has two states, since it can be turned off $N_{ES} = 0$ and off $N_{ES} = 1$, it is possible to define the total number of different configurations:

$$N_{conf} = N_{PF} \times N_{GN} \times N_{ES} \tag{4.6}$$

A matrix of configurations is generated by the values of the vehicle configurations defined as the combination of the working modes (gear number and power flows) and state variables (engine state and battery state of charge). The state variables are the variables which are essential to define the state of the main components of the architecture, for this application we will consider:

- The engine state,
- The battery SOC that can vary between a maximum and a minimum value SOC_{max} and SOC_{min} respectively. Furthermore, considering that, in the study case, the battery is not externally rechargeable, the SOC has to be kept as close as possible to the initial one, namely SOC_{start} or SOC_{target}.

4.3 Internal combustion engine

The engine used for this application is a Compression Ignition (CI) engine, namely combustion occurs due to compression of a charge formed by air and burned gas. Fuel is injected at a high-pressure level so that it atomizes, and this is what causes the spontaneous combustion (with no external energy source, such as Spark Ignition SI engines). CI engine are characterized by four operative phases, represented in Figure 17:

1. Suction: intake valves open to allow air to enter. The piston goes from the upper dead centre (PMS) to the lower dead centre (PMI), during this journey the connecting rod makes one stroke and the crank rotates 180°. As it descends, it

creates a strong depression in the combustion chamber; and by filling the fuel by an injector, the chamber fills up,

2. Compression: the valves close and the piston rises compressing the fuel inside the combustion chamber. Pressures reached at the end of this phase for CI engines are higher than those of SI engines to allow the self-ignition of the mixture,
3. Expansion: in this phase, ignition occurs spontaneously due to the high temperature and pressure formed at the end of compression. After combustion, gases at very high pressure and temperature have formed inside the chamber, pushing the piston down to the PMI. Since all the pistons are connected to each other through the crankshaft, while one goes up the other goes down, and the mechanism goes forward,
4. Exhaust: The piston, which has gone to the PMI after expansion is done, rises and emits the gases through the opening of the exhaust valves, which evacuate the gas from the cylinder, preparing it for a new cycle. The combustion residues are introduced into the exhaust manifold, connected to the exhaust system.

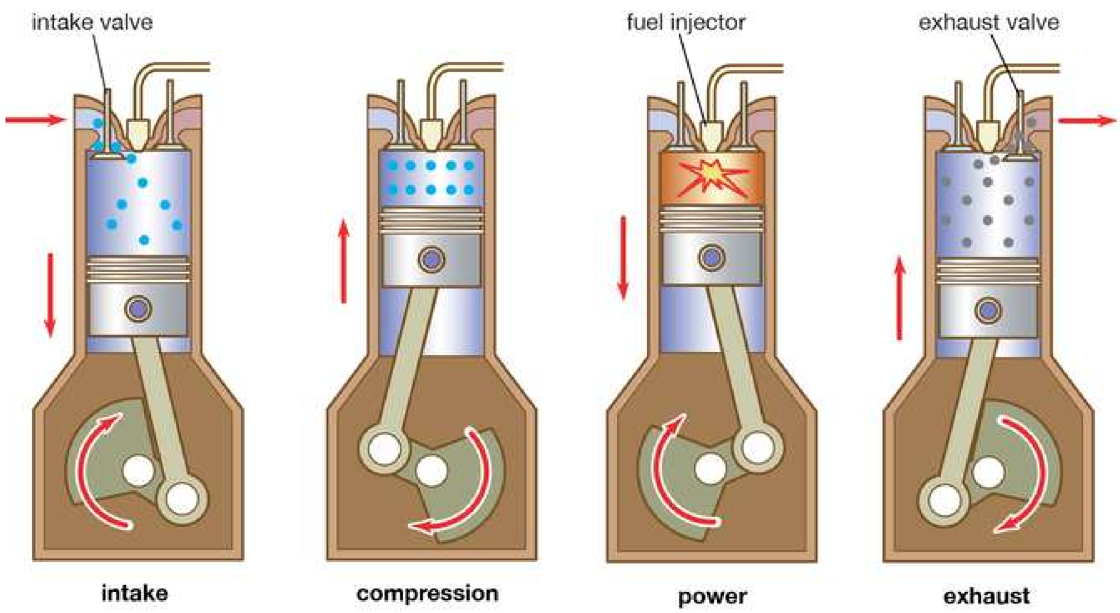

Figure 17-CI engine phases [7]

Diesels have the advantage to be able to deliver constant power for long time periods, they suffer less wear and can operate at higher efficiency. The diesel engine's high torque, combined with hybrid technology, may offer substantially improved mileage and autonomy for the hybrid vehicles. Nowadays, diesel-electric hybrid drivetrains are mostly common in commercial vehicles such as buses or delivery trucks. Nonetheless, diesel engines emit the following pollutants:

- NOx due to high temperatures reached in the diffusive combustion phase and the instantaneous reduction due to the apparent heat release rate (AHRR),
- Unburnt hydrocarbons (HC) due to the zone in the combustion at the border of the spray where the mixture is too lean, due to a rich mixture at the core of the spray, overmixing, overfueling or spray impingement,
- Particular matter (PM) or soot particles due to agglomeration of carbon particles produced in the hydro-carbon cracking phase.

The maps of the engine, the fuel consumption map and NO_x emission map are given in advance by the MATLAB tool, so look-up tables are used so that the mass flow rate of fuel $\dot{m}_{fc}$ is evaluated by interpolating 2D map function of engine power and speed, as follows:

$$\dot{m}_{fc} = \dot{m}_{fc}(P_{ICE}, \omega_{ICE}) \tag{4.7}$$

That also allows to obtain CO2 emission:

$$\dot{m}_{CO_2} = 2.65 \cdot \frac{\dot{m}_{fc}}{\rho} \tag{4.8}$$

With ρ representing the density of the fuel.

4.4 Electric Machines

The electric machine model of the tool simulates the power conversion from the electric to the mechanical form, and vice-versa, considering the energy losses by means of efficiency maps, which are functions of the machine power and speed. The maps related to these conversions are pre-calculated:

$$P_{EM,e} = \eta_{EM,m2e}\left(P_{EM,m}, \omega_{EM}\right) \cdot P_{EM,m} \tag{4.9}$$

$$P_{EM,m} = \eta_{EM,e2m}\left(P_{EM,e}, \omega_{EM}\right) \cdot P_{EM,e} \tag{4.10}$$

The power is bounded as function of the rotational speed ω_{EM} and this will influence the feasibility of the electric machine according to the power demand.

4.5 Driving cycles

ECMS have been tested in different driving cycles, precisely WHVC, FTP-72 and JC08, the cycles will be briefly described in this section.

WHVC (World Harmonized Vehicle Cycle) is a chassis dynamometer test with 1800 seconds duration. It is made up by three phases:

- The first 900 seconds represent urban driving with an average speed of 21.3 km/h and a maximum speed of 66.2 km/h. This segment includes frequent starts, stops and idling,
- The following 481 seconds represent rural driving with an average speed of 43.6 km/h and a maximum speed of 75.9 km/h,
- The last 419 seconds are defined as highway driving with average speed of 76.7 km/h and a maximum speed of 87.8 km/h.

FTP-72 (Federal Test Procedure) is a dynamometer urban route test cycle of 1372s with frequent stops. It reaches a maximum velocity of 91.25 km/h, has an average speed of 31.5 km/h and is made up by two phases:

- The first 505 seconds phase with a cold start and 41.2 km/h average speed,
- Second 867 seconds phase.

JC-08 (Japan Cycle) is chassis dynamometer test cycle for light vehicles representing driving in city traffic with frequent idling periods and alternating accelerations and decelerations. It has a duration of 1204 seconds with a 34.8km/h average speed (excluding idle) and a maximum speed of 81.6km/h. There is an initial idle for both cold and warm start. A visual representation of the cycles tested can be seen in Figure 18:

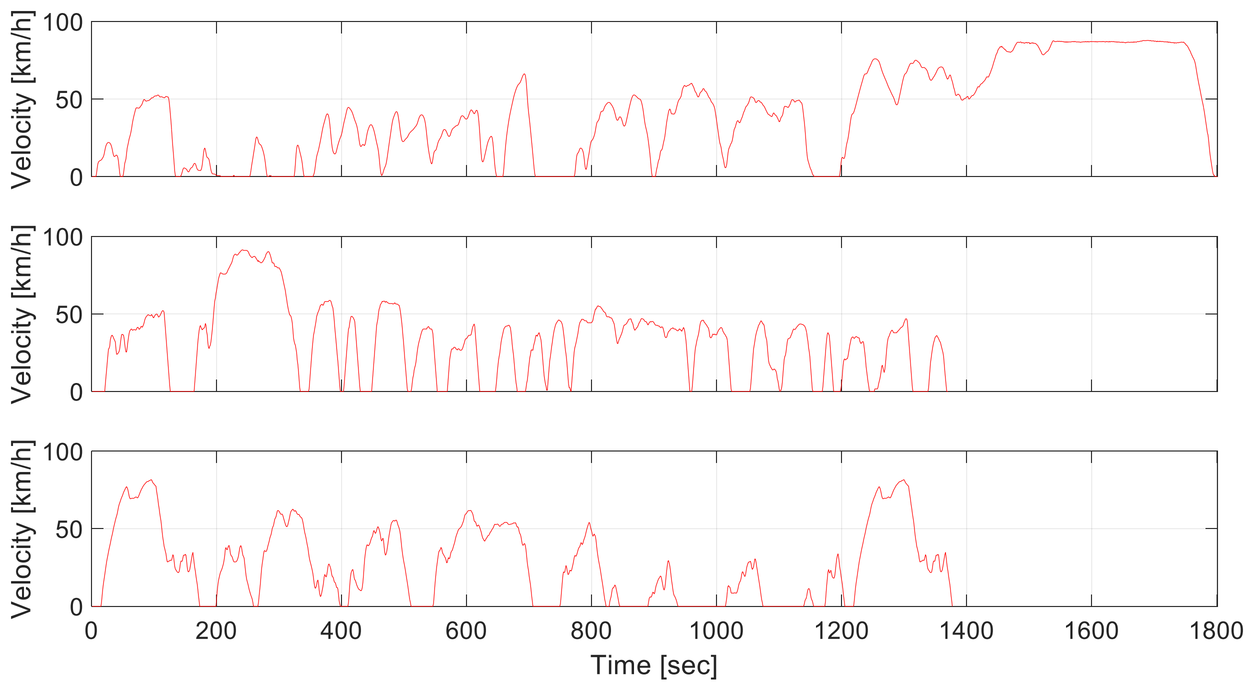

Figure 18-WHVC, FTP-72 an JC08 driving cycles

All these cycles are inserted in the input parameters of the MATLAB tool and tested. The idea is to test the controller ECMS in different driving conditions, both for the driving cycle for the reference vehicle (WHVC) as well as a more aggressive accelerations cycle (FTP-72) and a frequent idles and start-ups typical of urban environment (JC08). In this sense it is possible to demonstrate that ECMS control is extendable also to different driving conditions.

4.6 Battery

The model utilizes Lithium-Ion (Li-Ion) batteries as power storage device. A structure of the battery and how is sized will be described in this section, alongside with parameters that can be tuned by the user. Essentially, the tool calculates the maximum power required to the battery, given the maximum power of all the electric machines and Power-to-Energy ratio (P_E ratio), defined by the user:

$$P_E = \frac{P_{max,el}}{P_{max,batt}} \tag{4.11}$$

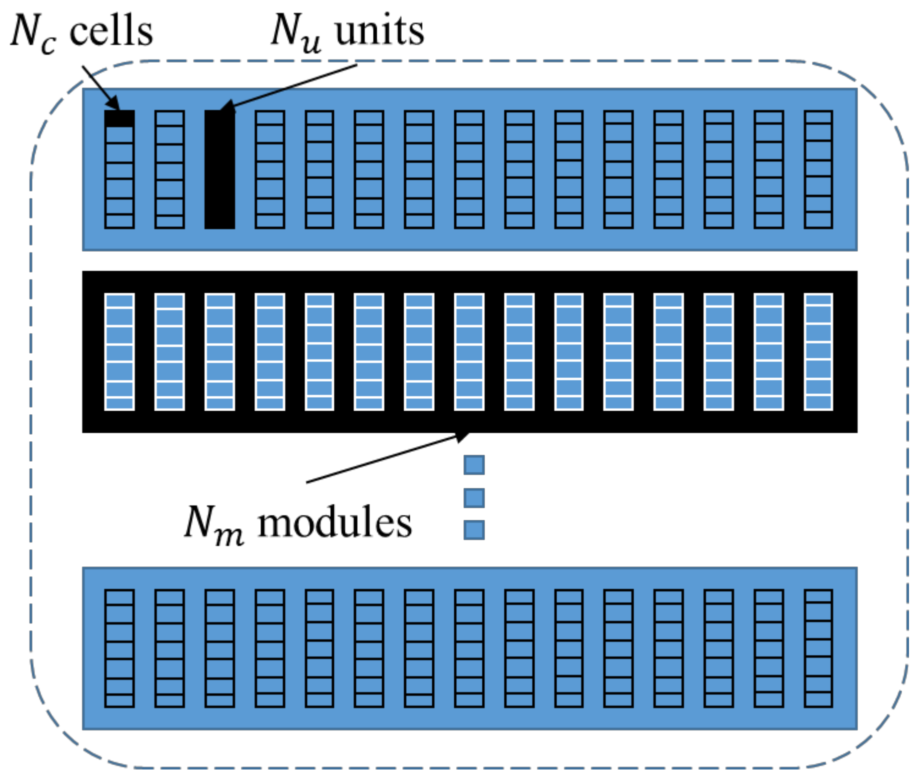

Figure 19-Battery model of the MATLAB tool

The tool is able to determine the number of cells and how to connect them, starting from the battery nominal voltage and a reference cell whose specifications are an input to the tool. The data specified as input in the battery datasheet are the cell nominal voltage V_c, the cell nominal capacity C_c, the number of cells in a unit N_c, the nominal reference battery voltage V_{nom}, the battery mass $M_{batt,ref}$, the battery total number of cells $N_{tot,ref}$ and the maximum and minimum discharge rates. Firstly, P_E ratio used to get the energy of the battery E_{batt}, by dividing the EM peak power by the P_e ratio:

$$E_{batt} = \frac{\sum_i P_{EMi,peak}}{P_E} \tag{4.12}$$

Then the tool implements the following equations, in order to determine number of units constituting a module, and the number of modules itself (Figure 17), through the following equations:

$$C_u = C_c \tag{4.13}$$

$$C_{batt} = \frac{E_{batt}}{V_{nom}} \tag{4.14}$$

$$N_{pu} = \frac{C_{batt}}{C_u} \tag{4.15}$$

$$V_u = V_c \cdot N_c \tag{4.16}$$

$$V_m = V_u \tag{4.17}$$

$$N_{sm} = \frac{V_{nom}}{V_m} \tag{4.18}$$

Battery model is based on the internal resistance model, following the scheme of Figure 18:

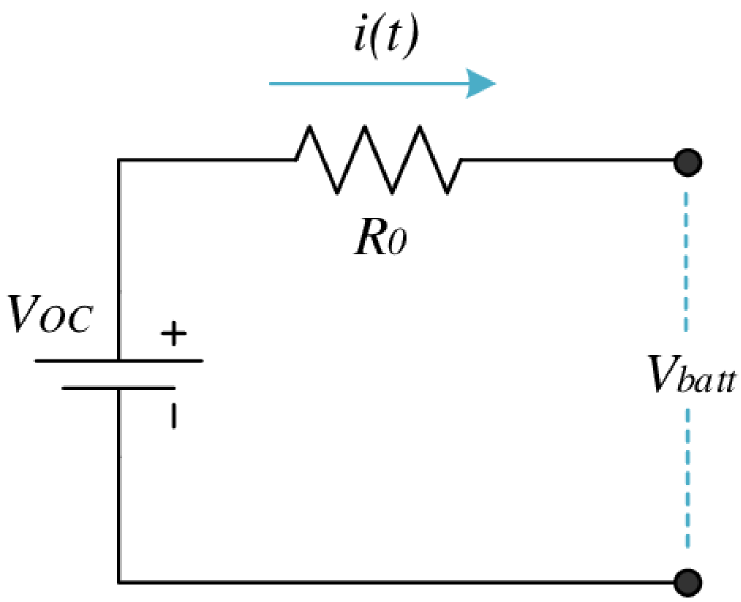

Figure 20-Battery internal resistance model

In this way, it is possible to obtain the SOC of the battery, as a function of the battery open circuit voltage V_{oc} and its internal resistance R_0. The reference battery's open circuit voltage

$V_{OC_{ref}}(SOC)$ and internal resistance $R_{0_{ref}}(SOC)$ characteristics are provided to the tool in the components data generation phase. Then, the characteristics for the current layout are determined by the tool as follows:

$$V_{OC}(SOC) = V_{OC_{ref}}(SOC) \cdot N_{sm} \cdot N_c \tag{4.19}$$

$$R_{eq}(SOC) = R_{eq_{ref}}(SOC) \cdot \frac{N_{sm} \cdot N_c}{N_{pu}} \tag{4.20}$$

Maximum current in charge and discharge are obtained by the maximum charge and discharge rate, as follows:

$$I_{max,ch} = \frac{C_{batt}}{1h} \cdot C_{max,ch} \tag{4.21}$$

$$I_{max,dis} = \frac{C_{batt}}{1h} \cdot C_{max,dis} \tag{4.22}$$

Power limits curves are finally used with $V_{OC}(SOC)$ and $R_{eq}(SOC)$ to get the values of the battery current I_{batt} and SOC at each time step:

$$I_{batt} = \frac{V_{batt} - \sqrt{V_{batt}^2 - 4 \cdot R_{batt} \cdot P_{batt}}}{2 \cdot R_{bat}} \tag{4.23}$$

$$SOC_t = SOC_{t-1} - \int \frac{I_{batt}}{C_{batt}} \cdot dt \tag{4.24}$$

5. ECMS

The idea behind this work is to implement a fast and reliable way to control HEVs, capable to be on-board implementable. As discussed, different strategies can be used, but methods such as DP or PMP are not implementable online, due to their need to know the whole set of information in advance and long calculation times. On the other hand, Equivalent Consumption Minimization Strategy (ECMS) represents a promising approach for a real-time control and a development of the algorithm is proposed in this thesis, alongside with a fast method to calibrate the Equivalence Factors. This kind of controller is implementable in the supervisory control of the vehicle, that defines the points of the control and communicates them to the engine control unit, combined with the battery management system. ECMS has been deeply analyzed and tested yet and represents a commonly approved tool to solve the Energy Management Problem for HEVs since it is based only on the instantaneous information by the vehicle. The objective of this section is to show an application of ECMS in different powertrain configurations and driving scenarios with dedicated advanced features that increases the accuracy and efficiency of the control. Also, a fast way to find the optimal control parameters will be proposed, in order to reduce the calibration time and make the algorithm implementable on-board.

5.1 ECMS formulation

The idea behind ECMS is the application of the PMP for a dynamic problem. The original formula derived from an engineering intuition that has been proved being successful in different application, even without formal proof of optimality, due to the fact that is strictly related to PMP. Recalling the Hamiltonian function (Eq. 3.6) can assume the meaning of *equivalent fuel consumption* that can be intended as a sum between the actual fuel consumption from the ICE and an equivalent fuel consumption from the EM, with the same units of measurements, dependent from the SOC variation. In this sense, the co-state parameter $\lambda(t)$ can be seen as the link between the fuel use and the battery use, and more intuitively an Equivalence Factor (EF) is defined:

$$s(t) = -\lambda(t)\frac{Q_{lhv}}{E_{batt}} \tag{5.1}$$

With Q_{lhv} representing the lower heating value of the fuel and E_{batt} representing the energy capacity of the battery. Given this, the Hamiltonian function can be rewritten as the equivalent consumption:

$$H(x,u,\lambda) = \dot{m}_{eqv}(x,u,s) = s(t) \cdot \frac{Q_{lhv}}{E_{batt}} \cdot f(x,u) + \dot{m}_f(u) \tag{5.2}$$

Equation (5.2) represents the starting point for ECMS, that leads to the formulation with the following objective function [9]:

$$J_t = \dot{m}_{ice}(P_{ice}(t)) + \varsigma(P_{em}(t)) \tag{5.3}$$

With:

$$\varsigma(P_{em}(t)) = \gamma \cdot s_{dis} \frac{1}{\eta_{batt}(P_{em})\eta_{em}(P_{em})} \frac{P_{em}(t)}{H_{LHV}} + (1-\gamma) \cdot s_{chg} \cdot \eta_{batt}(P_{em}) \cdot$$
$$\cdot \eta_{em}(P_{em}) \frac{P_{em}(t)}{H_{LHV}}$$

$$with\ \gamma = \frac{1+sign(P_{em}(t))}{2} \tag{5.4}$$

In which $\varsigma(P_{em}(t))$ represents the fuel equivalent of the electrical energy, s_{chg} and s_{dis} are the Equivalence Factors (EFs) for charge and discharge, respectively. The condition of optimality can now be defined:

$$\{P_{ice}^{opt}(t), P_{em}^{opt}(t)\} = \arg\min J_t \tag{5.5}$$

$$\begin{cases} \{P_{ice}^{opt}(t) = 0, P_{em}^{opt}(t) = P_{req}\} & if\ P_{req} \geq 0 \\ \begin{cases} P_{req}(t) = P_{ice}(t) + P_{em}(t) \\ SOC_{min} < SOC(t) < SOC_{max} \\ 0 \leq P_{ice}(t) \leq P_{ice,max}(t) \\ P_{em,min}(t) \leq P_{em}(t) \leq P_{em,max}(t) \end{cases} & if\ P_{req} < 0 \end{cases} \tag{5.6}$$

In this case, SOC_{min} and SOC_{max} are defined by the interval [0.4 0.8]. EFs are the control parameters of ECMS, that have to be properly calibrated. The advantage of having two different parameters allows to calibrate them in order to get a precise charging/discharging behaviour, namely define the frequency in which it is preferred a charge sustaining or a charge depleting tendency, respectively. Performance of ECMS strongly depends on the value of the control parameters that are severely linked to the driving cycle, and a detailed calibration method will be shown in the next sections.

5.2 ECMS penalty function

As is known, a crucial parameter in HEVs control is the SOC through the cycle. As stated before, it is crucial, especially for non-plugin HEVs, to guarantee that SOC does not exceed an upper and a lower boundary and keep the SOC level as close as possible to the reference one. In this sense, a way of limit the SOC window, namely the difference between the values of the maximum and minimum SOC level reached through the cycle has been proposed. It consists of a penalty function, that gives a higher weight to all the power flows that lead to a SOC too different from the reference one [4]:

$$p(SOC) = 1 - \left(\frac{SOC(t) - SOC_{ref}}{\frac{SOC_{max} - SOC_{min}}{2}} \right)^a \tag{5.7}$$

With a representing the exponent of the penalty. The objective function becomes:

$$J_t = \dot{m}_{ice}(P_{ice}(t)) + \varsigma(P_{em}(t)) \cdot p(SOC) \tag{5.8}$$

In this way, when $p(SOC) < 1$, namely when the SOC is above the reference, the discharge is more probable whereas when $p(SOC) > 1$, SOC is over the reference value and the cost of the battery energy is increased to make its discharge less likely.

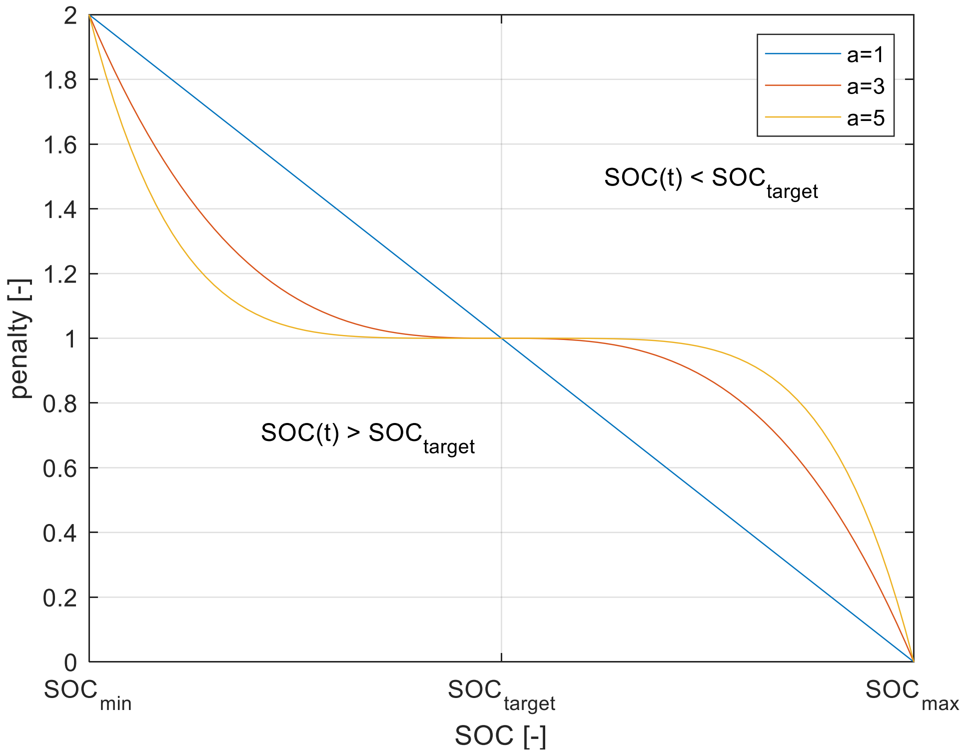

Figure 21-SOC Penalty function p(SOC)

In Figure 21, a detail of the influence of the exponent of the penalty function is shown. It is possible to underline that a higher exponent leads to a less severe penalty in proximity of the target SOC, for this application $a = 3$ is chosen.

5.3 ECMS EF calibration

As stated in the last chapter, performance of ECMS strongly depends on the EFs, that depend on the driving conditions and other parameters. Firstly, it is necessary to underline some criteria for defining optimal EFs. A proper EF pair is evaluated according to:

- CO_2 consumption, since the main task of the control strategy is to reduce emissions,
- Final SOC level, as it as to reach at least the target SOC,
- Minimum and maximum SOC level through the cycle (SOC window), as a too high SOC leads to higher consumption whereas low SOC level would not guarantee a pure electric take-off if the engine is turned off before the end of the mission,
- Power flow set-up, because pure electric, and power split are preferred with respect to the more fuel wasting power flows (pure thermal and especially battery charging)

Depending on different parameters, calibration of EFs is not an easy task. In literature, it is recommended to use the iterative method and find the pair that optimally satisfy all the constraints.

There is a trend that allows to have indications to tune the EFs, based on the distinction between two different processes:

$$\{s_{dis} \uparrow | s_{chg} \downarrow\} \qquad charge\ depleting\ trend$$
$$\{s_{dis} \downarrow | s_{chg} \uparrow\} \qquad charge\ sustaining\ trend$$

Since this selection process is still complex, in the following sections a fast way to calibrate EFs will be shown consisting in the creation of an EFs set and a unique parameter in order to select the best EF pair.

5.3.1 Model Based Calibration for EF calibration

In this part of the work, it was helpful to use the Model Based Calibration toolbox (MBC) in MATLAB. This method allows to evaluate calibration parameters when the output is made of a high amount of data. In particular, Design of Experiment (DoE) is chosen for EF calibration because is a useful tool to evaluate factors influencing a process and the output, especially for complex nonlinear systems. It defines a proper testing plan and allows to save time enabling to perform only test that are needed to determine the output response. It leads to a reduction of systematic errors and distortions, full exploration of factorial space, and reduction of number of tests to be made. The idea is to control the calibration parameters and check the influence on the variation on one or more desired outputs, it is useful for addressing problems associated with designing complex control, signal processing and communication systems. The design editor allowed to choose Space Filling design, that is recommended when there is a low knowledge of the system that has to be studied. Since EF have influence on different parameters, Space Filling is the most suitable technique for generating a proper set. In fact, space filling design creates creating a simpler surrogate model of a highly complex deterministic computer simulation model, it minimizes bias both by spreading the design points out as far from each other as possible and by spacing them evenly over the design region. Also, space filling designs collect data in such as a way as to maximize coverage of the ranges of the factors and this characteristic is necessary since the control strategy is very case-sensitive and all possible pairs have to be tested. This aspect is also ensured by using a Sobol sequence that is a quasi-random low-discrepancy sequence which forms a finer uniform partition of the range set and then reorder the coordinates in each dimension and is able to cover the space more evenly. An example of quasi-random sequency is shown in Figure 22:

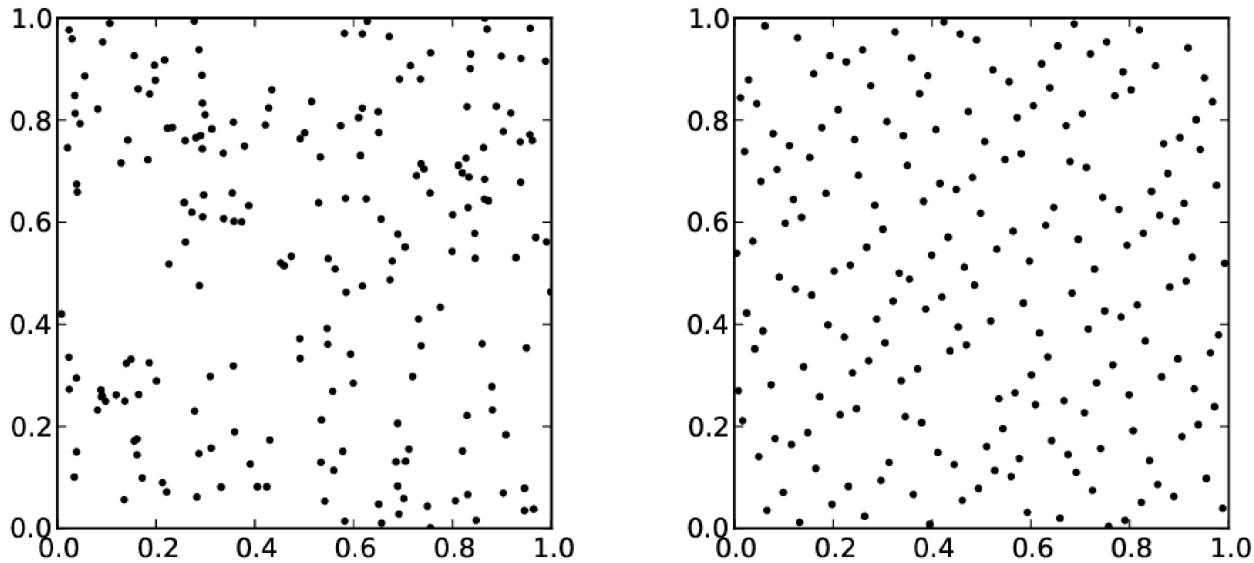

Figure 22-Differences between Pseudo-random (left) and Quasi-random (right) sequence

As a first step, it is necessary to choose a proper EF range to be tested, in the considered case, each point of the sequence represents an EF pair, with discharging factor on horizontal axis and charging factor on the vertical axis. Referring to literature, the EF range have been set to the interval [2,3]. To have proper accuracy, since the controller is very case sensitive, 1000 points have been chosen. Also, a first condition with $s_{chg} > s_{dis}$ has been imposed in order to enhance a charge sustaining trend. The EF set chosen for this application can be seen in Figure 23, in which each point represents an EF pair:

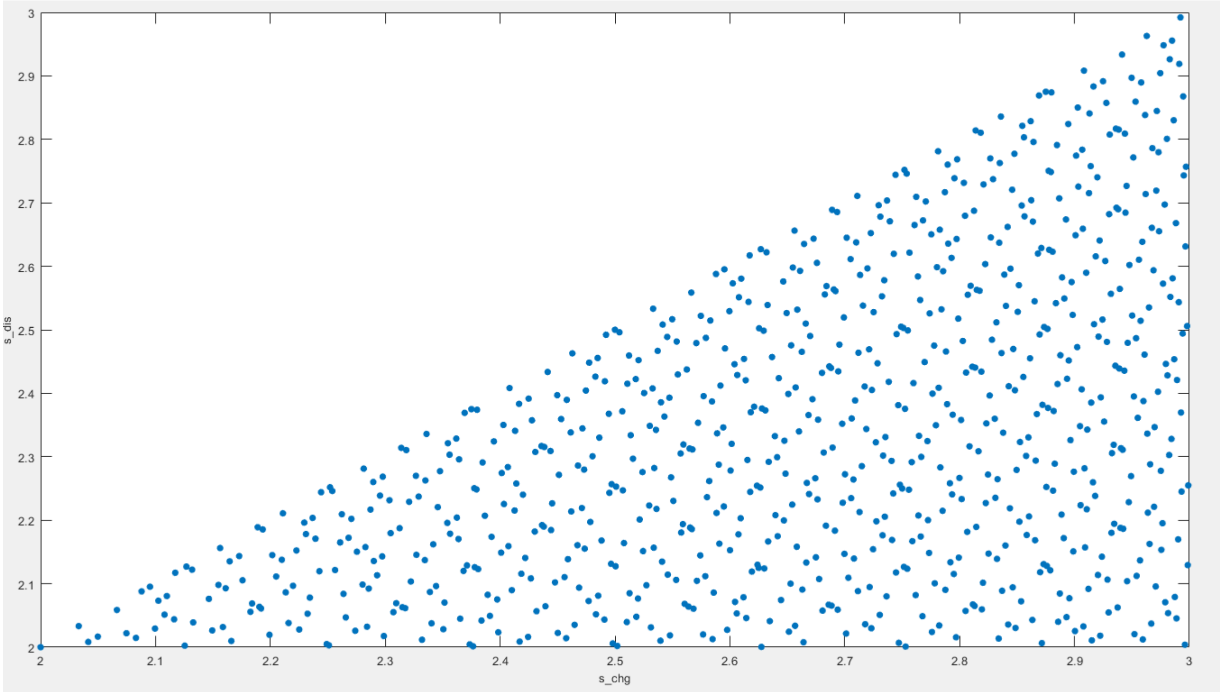

Figure 23-EF set obtained by DoE with 1000 points

5.3.2 EFs correlation

Since the number of simulations to calibrate equivalence factor is very high, a way to reduce them is here proposed. The idea is to find a relationship between the EFs, and so to halve the number of control parameters with a consequent reduction of the tuning time. This can be done using the relationship between ECMS and the power based PMP formulation for which the Hamiltonian function becomes [4]:

$$H = P_{fuel} + \lambda \cdot P_{ech} \tag{5.9}$$

Recalling also the fuel consumption defined with the equivalent from the battery:

$$\dot{m}_{f,eqv} = \dot{m}_f + \frac{s}{Q_{lhv}} \cdot P_{batt} \cdot p(SOC) \tag{5.10}$$

Multiplying all the terms for Q_{lhv}:

$$P_{eqv} = P_{fuel} + s \cdot P_{batt} \tag{5.11}$$

P_{batt} is the net electrical power at the battery terminals, while P_{ech} represents the electrochemical power, the power correlated to the effective SOC variation. It can be assumed that the relation between this quantity and the electrical power can be modeled with the battery charge/discharge efficiency η_{batt}:

$$P_{ech}\big(SOC(t), P_{batt}(t)\big) = \begin{cases} \frac{P_{batt}(t)}{\eta_{batt}(SOC, P_{batt})} \\ \eta_{batt}(SOC, P_{batt})P_{batt}(t) \end{cases} \tag{5.12}$$

In this way, the ECMS and the Hamiltonian are linked by the co-state λ:

$$s_{chg} = \lambda\eta_{batt}$$
$$s_{dis} = \frac{\lambda}{\eta_{batt}}$$

By which:

$$s_{chg} = \eta_{batt}^2 s_{dis} \tag{5.13}$$

In this way there is no necessity of different equivalence factors, and the algorithm is made less computationally heavy and is easier for on-board implementation. In Chapter 6, where results of ECMS formulation will be showed, this correlation will be applied, and a proof of its efficiency will be provided.

5.3.3 Criteria used to evaluate the optimal EFs

Once a proper EF set is obtained, it is necessary to find the optimal pair, that leads to the best results in terms of CO_2 and fuel consumption. It is important to state that the EFs strongly depend on the type of controller and design parameters (e.g. Engine Size, Final drive speed ratio, Size of the battery…), so each configuration has its optimal EF pair. The criteria for evaluating the optimality of an EF pair are the following in increasing importance:

- CO_2 consumption, that has to be as low as possible,
- Final SOC level that has to reach the reference value (SOC_{start}),
- Minimum and maximum SOC level trough the cycle SOC_{min} and SOC_{max},
- Level of battery charging and power split strategies through the mission.

As stated, the main task of the ECMS controller is to reduce the fuel consumption, but this objective has also to be considered in relation to other parameters. Regarding final SOC level, it is crucial that the vehicle should end its driving cycle with a charging state as near as possible to the reference one in order to have sufficient battery charge for a pure electric take-off, once the engine is turned off. Also, for a non-plugin HEV the fuel consumption for a final charging level below the reference one would not be realistic, as the fuel consumed to take the battery to the reference level (for instance, through battery charging) should be taken into account. This aspect will be furtherly analysed in section 5.3.4. An example of this aspect can be seen in Figure 24:

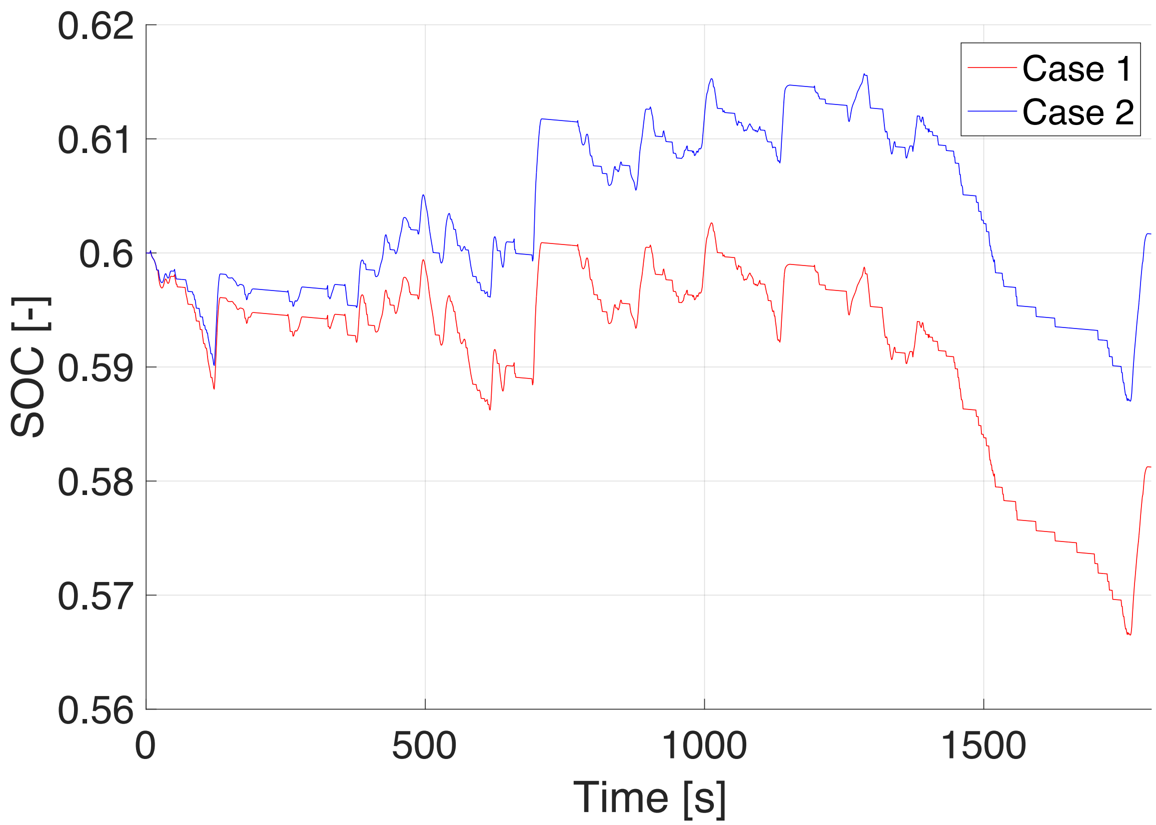

Figure 24-Example: SOC level through the mission

Case	SOCstart [-]	SOCfinal [-]	CO2ttw [g/km]
1	0,600	0,581	329.9
2	0,600	0.602	339.4

Table 4-CO2 consumption for the cases of Figure 22

In the example of Figure 24, the fuel consumption of the Case 1 is lower, due to the fact that the final SOC level is strongly below the reference one. This simulation is considered not realistic due to the fact that the fuel consumption to take the SOC level at the reference one is not taken into account and discarded on behalf of the Case 2. Regarding maximum and minimum SOC level through the cycle, the same reasoning showed above can be done. In fact, it is necessary to guarantee that the SOC level does not move away too much from the reference one through the whole cycle, considering that the engine could be possibly turned off at any moment and still, should guarantee the sufficient battery charge for a pure electric take-off. Also, power flow set-up should be taken into account, as by increasing the presence of battery charging strategy in time, the emissions increase as well. Since EF calibration is a tedious process, also due to the above presented constraints, it could be useful to find a unique output parameter that takes into account all of them and realistically calculates fuel consumption, for all the cases.

5.3.4 Equivalent CO_2 consumption

For practical applications, final SOC level can't possibly reach the reference one, it could reach a higher or a lower value either. In the latter case, the value of CO_2 and fuel consumption obtained are not realistic, due to the fact that the emissions due to the additional fuel waste to bring the final SOC level at the reference one is not considered. In this sense, it is necessary to correct the value of both fuel and CO_2 consumption, and this has been done according to the WLTP procedure (Worldwide harmonized Light vehicles Test Procedure-ECE/trans/180/Add.15). Corrected values of CO_2 and fuel consumption ($CO_{2_{ttw,eq}}$ and $FC_{ttw,eq}$, respectively) can be obtained as:

$$CO_{2_{ttw,eq}} = CO_{2_{ttw}} - K_{CO_2} \cdot \Delta E_{REESS_i} \tag{5.14}$$

$$FC_{ttw,eq} = FC_{ttw} - K_{Fuel} \cdot \Delta E_{REESS_i} \tag{5.15}$$

With K_{CO_2} and K_{Fuel} representing the correction coefficients for CO_2 and fuel consumption, respectively:

$$K_{CO_2} = \frac{n \cdot \Sigma E_{REESS_i} \cdot CO_{2\,ttw,i} - \Sigma E_{REESS_i} \cdot CO_{2\,ttw,i}}{n \cdot \Sigma E^2_{REESS_i} - (\Sigma E_{REESS_i}{}^2)} \tag{5.16}$$

$$K_{Fuel} = \frac{n \cdot \Sigma (E_{REESSi} \cdot FC_i) - \Sigma E_{REESSi} \cdot \Sigma FC_i}{n \cdot \Sigma E^2_{REESS_i} - \left(\Sigma E_{REESS_i}{}^2\right)} \tag{5.17}$$

With:

- n is the number of configurations (defined, in the case with the number of EFs tested),
- FC_i is the Fuel Consumption measured for the n-th configuration in L/100km,
- $CO_{2\,\mathrm{ttw},i}$ is the CO2 tank-to-wheel emission measured for the n-th configuration in g/km,
- E_{REESSi} is the electricity balance measured for the i-th Rechargeable Electric Energy Storage System (REESS) in Wh/km obtained as follows:

$$E_{REESSi} = \frac{SOC_{final} \cdot C_{tot} \cdot V_{batt}}{distance} \tag{5.18}$$

In which:

- C_{tot} is the nominal capacity of the battery in Ah,
- V_{batt} is the nominal voltage of the battery in V.

In (5.14) and (5.15), ΔE_{REESS_i} is change in the REESS energy content expressed as percentage:

$$\Delta E_{REES_i} = \frac{0.0036 \cdot RCB \cdot U_{REESS}}{E_{fuel}} \cdot 100 \tag{5.19}$$

- U_{REESS} is the nominal REESS voltage in V,
- E_{fuel} is the energy content of the consumed fuel in MJ,
- With RCB indicating the REESS balancing balance on the whole cycle in Ah:

$$RCB = C_{tot} \cdot \Delta SOC \tag{5.20}$$

With ΔSOC indicating the difference between final SOC level and the reference one.

According to ECE TRANS procedure, the correction coefficients K_{CO_2} and K_{Fuel} have to be obtained for each single layout varying only the calibration parameters (in our case the EFs) for each driving cycle tested. In the present work WHVC, FTP 72 and JC08 have been tested with two different engine sizes (4,5 and 3L). Both correction factors have to be calculated for each phase of the driving cycle (e.g., considering WHVC: urban, rural, motorway) and a unique value, assigned the engine size and the driving cycle, has been obtained considering a weighted average based on the temporal duration of each phase over the whole cycle. Regarding number of configurations n, firstly all EF set obtained by DoE has been considered, and then only the N feasible simulations for each phase of the driving cycle have been considered. For sake of clarity, an example of the procedure for the calculation of K_{CO_2} in WHVC driving cycle case, is proposed in Figure 24:

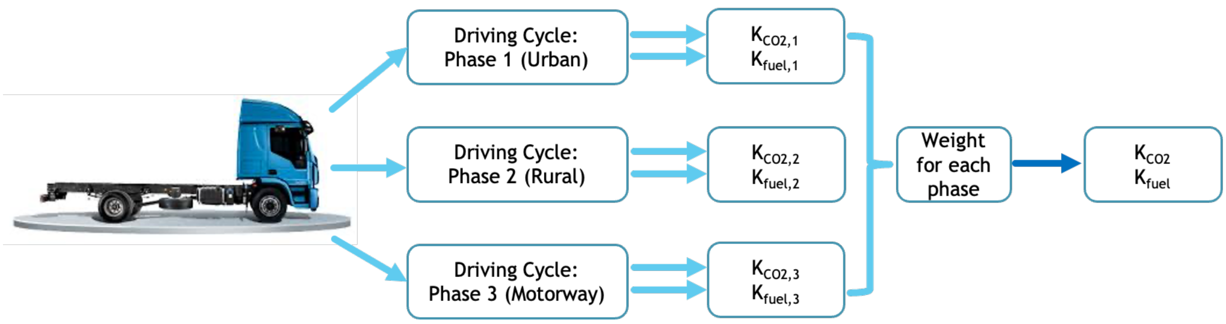

Figure 25-Example of KCO2 calculation for WHVC

4,5L

PHASE				WF (∑=1)
URBAN				0.5
N	357	kCO2urban	0.60344	0.30172
		kFuelurban	0.02384	0.01192
RURAL				0.27
N	432	kCO2rural	0.60415	0.16312
		kFuelrural	0.02387	0.00645
MOTORWAY				0.23
N	358	kCO2motor	0.57287	0.13176
		kFuelmotor	0.02263	0.00521

WHVC	
kCO2	0.59660
kFuel	0.02357

Figure 26- Detail on KCO2 calculation for 4,5L engine displacement on WHVC cycle

Driving cycle	KCO2 [g/km/Wh/km]	KFuel [l/100km/Wh/km]
WHVC	0.59660	0.02357
FTP-72	0.58947	0.02329
JC08	0.56726	0.02241

Table 5-Results on correction coefficients for fuel and CO2 for 4,5L

5.3.5 Optimal choice of EF pair

Once obtained the correction coefficients, it is possible to underline the way the optimal EF pair, for each driving cycle and engine size, is chosen:

1. A set of EFs is created with DoE as showed in section 5.3.1 and the whole set is simulated for assigned driving cycle and engine size,
2. All results are filtered considering only the simulations leading to: $$SOC_{target} - \varepsilon < SOC_{final} < SOC_{target} + \varepsilon \quad with\ \varepsilon = 5\%$$
3. All results are sorted in ascending order of ${CO_2}_{ttw,eq}$ and the EFs with the lowest value of ${CO_2}_{ttw,eq}$ are chosen as optimal ones for the assigned engine displacement and driving cycle,
4. A final check on final SOC level and SOC window is done.

It is necessary to underline that ${CO_2}_{ttw,eq}$ value allows a fast and fine search of an optimal EF pair, since the simulation with the lowest ${CO_2}_{ttw,eq}$ value is considered as the best compromise between the criteria chosen in section 5.3.3. A proof of this aspect is shown in Figure 24:

EngDispl [L]	s_chg[-]	s_dis[-]	Co2ttw [g/km]	CO2ttw,eq [g/km]	SOCstart [-]	SOCfinal [-]	
4,4538	2,1806	2,4162	338,55	338,65	0,6000	0,59984	Case *a*
4,4538	2,1793	2,4147	338,06	338,76	0,6000	0,59882	
4,4538	2,1802	2,4157	338,06	338,76	0,6000	0,59882	
4,4538	2,1775	2,4128	337,81	338,83	0,6000	0,5983	
4,4538	2,178	2,4133	337,81	338,83	0,6000	0,5983	
4,4538	2,1762	2,4113	337,61	338,88	0,6000	0,59787	
4,4538	2,1753	2,4104	336,72	339,12	0,6000	0,59598	
4,4538	2,1736	2,4084	335,98	339,37	0,6000	0,59435	
4,4538	2,1815	2,4172	339,4	339,4	0,6000	0,60166	
4,4538	2,1723	2,4069	334,82	339,72	0,6000	0,59186	Case *b*
4,4538	2,1828	2,4187	339,75	339,75	0,6000	0,60247	
4,4538	...	...	...	...	...	...	

Figure 27-Optimal choice of EF pair example

All results are showed for increasing value of $CO_{2_{ttw,eq}}$:

- in Case *a*, the EF pair leads to the lowest $CO_{2_{ttw,eq}}$ value and this also brings to a final SOC close to the reference one,
- in Case *b*, the EF pair leads to a lower $CO_{2_{ttw}}$ with respect to Case *a* but a lower final SOC, that makes the equivalent emission value $CO_{2_{ttw,eq}}$ higher with respect to Case *a* and consequently Case *b* is discarded.

In any case, as proved, it is possible to directly seek the lowest $CO_{2_{ttw,eq}}$ value and define its EFs as the optimal ones.

5.4 Results

In this section, ECMS algorithm in an application for HEVs energy management strategy results for the reference configuration will be shown (4,5 L engine size) and a comparison between the correlated EFs relation and the uncorrelated EFs will be proposed, to proof the validity of the correlation with a consequent lower number of calibration parameters. Also, comparison with the benchmark control strategy DP as well as comparison with pure thermal model will be shown, in order to present the relative differences in terms CO_2 emission. The output data to be evaluated will be:

- SOC trend through the whole driving cycle,
- $CO_{2_{ttw}}$ and $CO_{2_{ttw,eq}}$ results,
- Power flows through the cycle,

- Delta SOC, obtained as follows:

$$deltaSOC = SOC_{final} - SOC_{start} \tag{5.21}$$

5.4.1 Uncorrelated and correlated EFs comparison

In this chapter the results for the most optimal EF pair for the tested cycles (WHVC, FTP 72 and JC08) and the reference configuration (4,5L) will be presented. A comparison between the correlated and the uncorrelated EFs (called ECMS) relation is showed, with the objective to reduce the number of control parameters and, consequently, calibration time. The validity of the correlated relation between EFs will be validated directly on the results with a comparison directly on the results obtained by correlated and uncorrelated ECMS formulation.

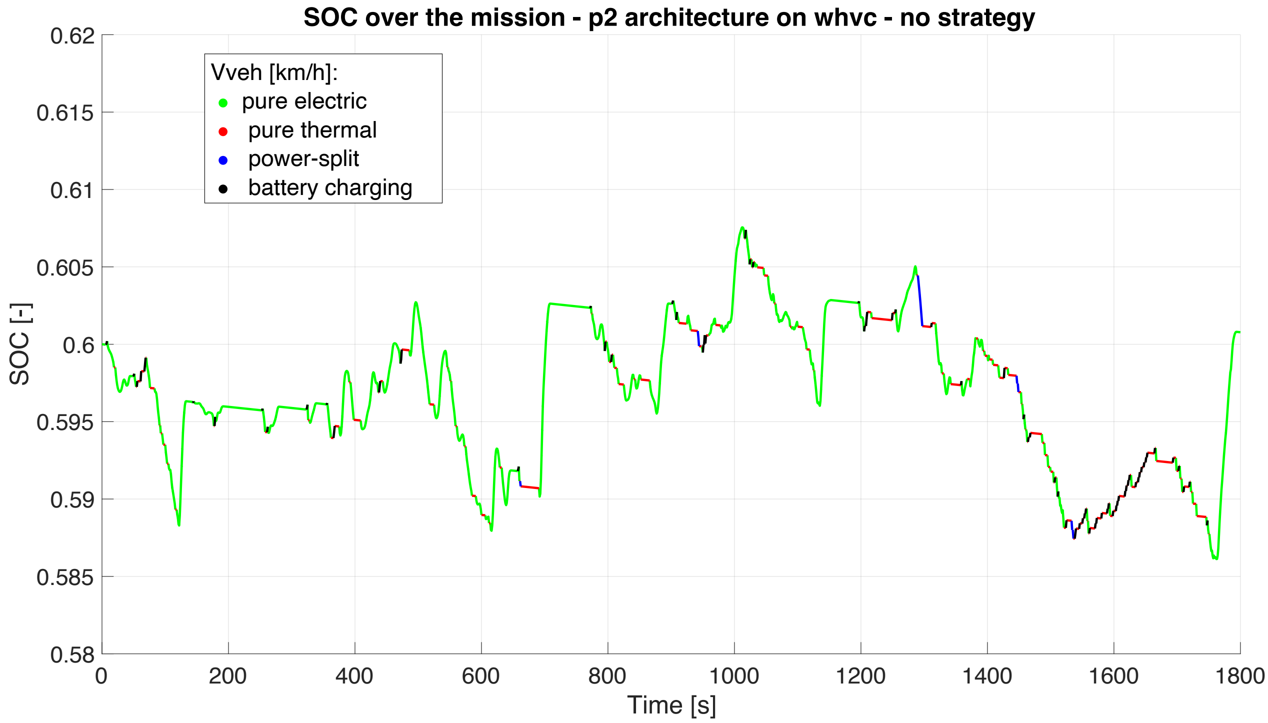

Figure 28-SOC level through the cycle, ECMS 4,5L on WHVC cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	PE [%]	PT [%]	PS [%]	BC [%]
ECMS	2.4421	2.3806	340.36	340.36	0.600	0.585	0.608	0.000	60.44	34.17	0.78	4.61

Table 6-Results uncorrelated ECMS 4,5L on WHVC

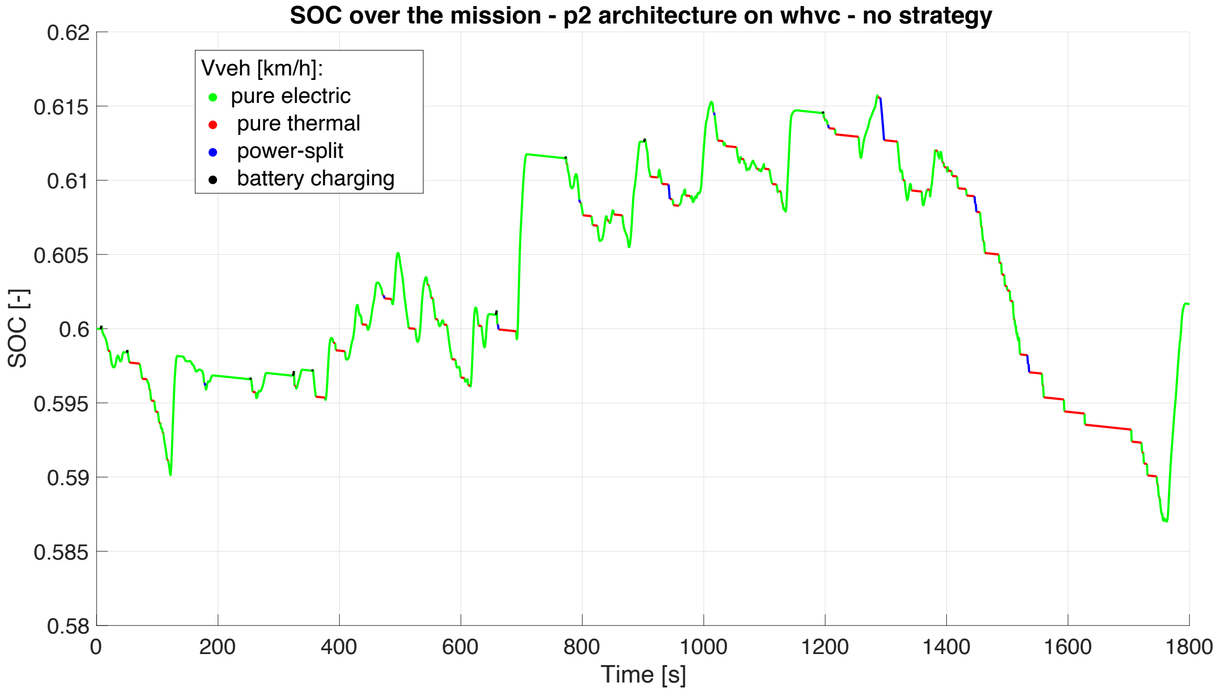

Figure 29-SOC level through the cycle, correlated ECMS 4,5L on WHVC cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	PE [%]	PT [%]	PS [%]	BC [%]
ECMS corr	\	2.4172	338.26	338.60	0.599	0.585	0.615	-0.001	57.28	40.94	1.00	0.78

Table 7- Results correlated ECMS 4,5L on WHVC

Now a comparison between the correlated and uncorrelated formula is proposed, alongside with the benchmark control strategy DP in the same WHVC cycle:

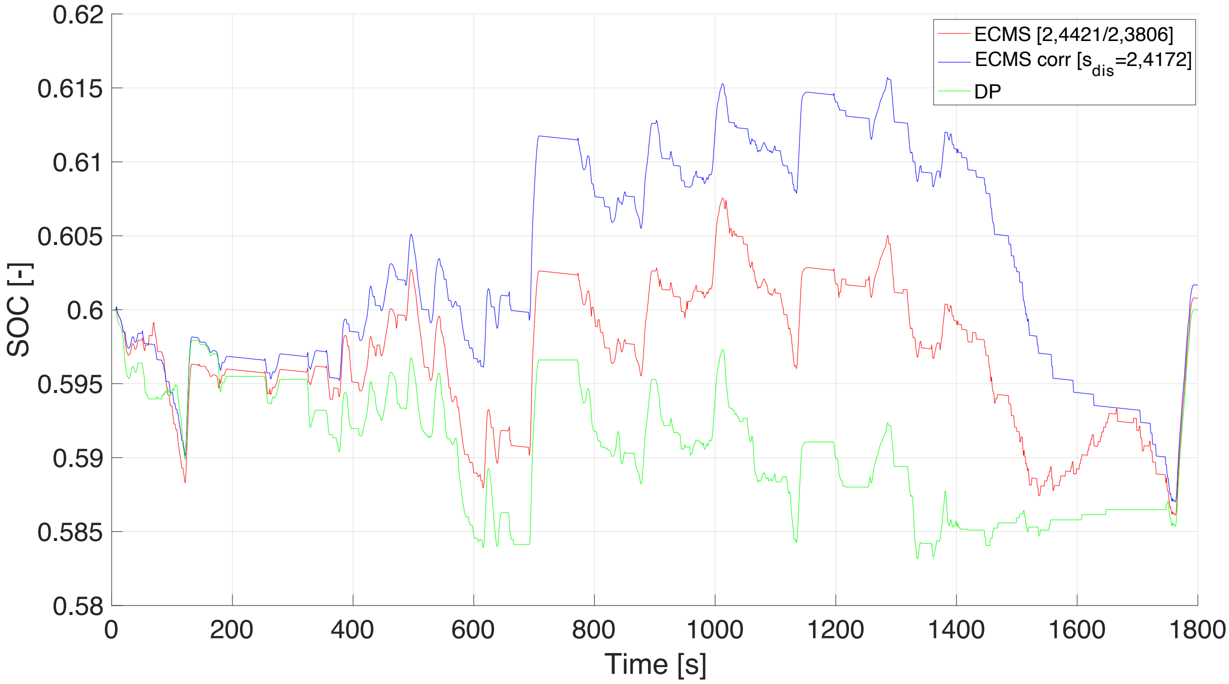

Figure 30-Comparison between correlated, uncorrelated EFs and DP for 4,5L on WHVC cycle

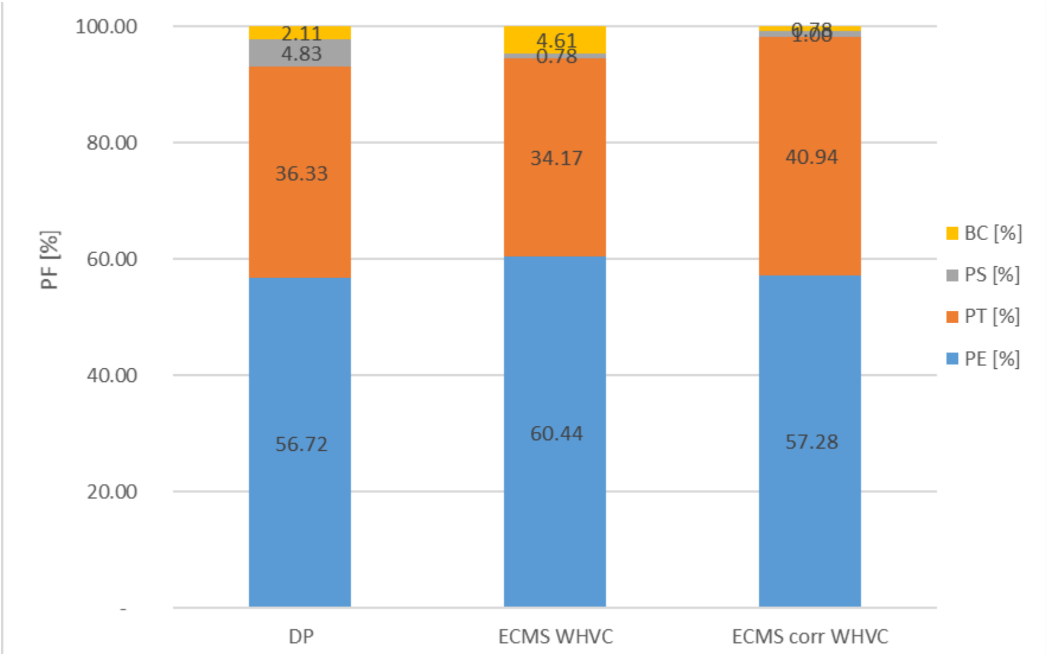

Figure 31-Detail on power flow strategy for DP, ECMS and ECMS corr on 4,5L WHVC cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	ΔCO2DP [%]	ΔCO2PT [%]
DP	\	\	337.86	337.86	0.600	0.584	0.600	0.000	0.00	-14.15
ECMS	2.4421	2.3806	340.36	340.36	0.601	0.586	0.608	0.001	0.74	-13.52
ECMS corr	\	2.4172	338.26	338.60	0.599	0.585	0.615	-0.001	0.25	-13.94

Table 8-Results for DP, ECMS and ECMS corr on 4,5L WHVC

For the above showed results, it is possible to underline that SOC trends shown in Figure 28 and Figure 29 respect all the constraints of Eqs. 5.6 and a final SOC level close to the reference one is reached. ECMS in both cases and especially for the correlated formulation, leads to a low battery charging strategy, with a percentage duration over the whole cycle also lower that DP (0.78%). Regarding CO_2 consumption that is the main objective of the control strategy, comparing the results with the ones of DP for the same configuration and driving cycle, ECMS has 0,74% higher CO_2 consumption whereas correlated ECMS only 0,24%, still guaranteeing a reduction of consumption of 13,52% and 13,94% with respect to the pure thermal configuration. In order to move towards the validation of the correlated ECMS, to reduce number of parameters to be calibrated, now a comparison between ECMS, correlated ECMS and DP is showed for the same configuration (4,5L) on FTP 75 and JC08 driving cycles. Firstly, it is necessary to recalculate the correction coefficients K_{CO_2} and K_{Fuel}, indicated on Table 5 and tune again the EFs for the new driving cycles, considering that same optimal values for WHVC can't be extended for other cycles, as shown in Figure 32:

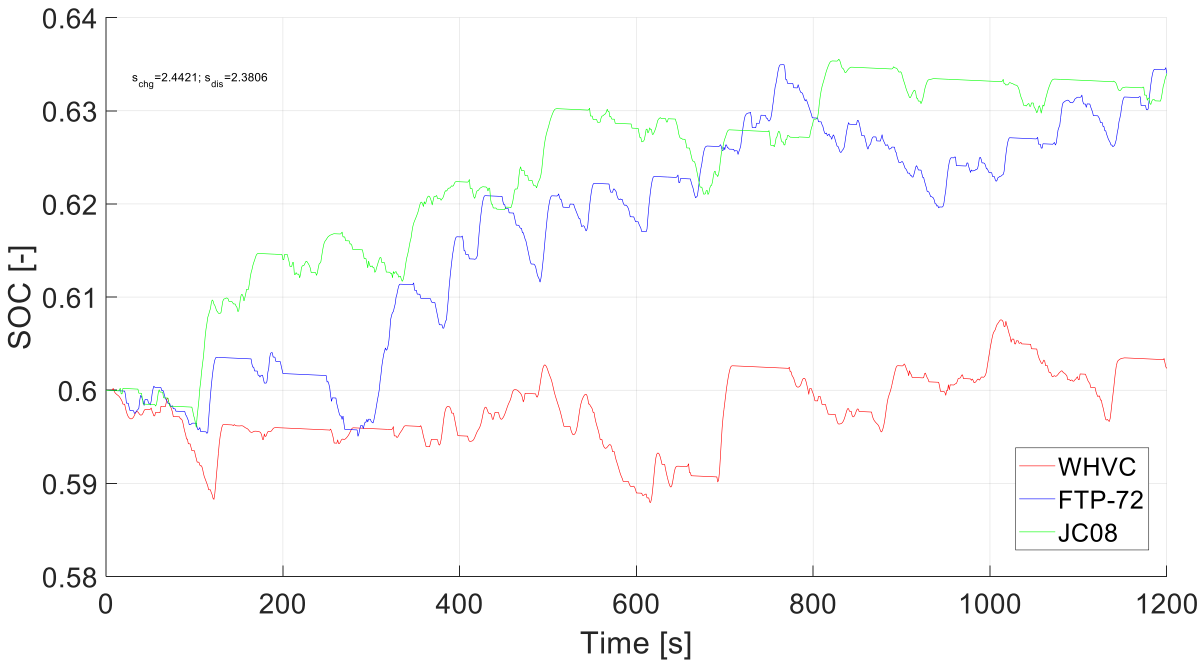

Figure 32-SOC trend comparison between WHVC, FTP 72, JC08 optimal WHVC EFs

In fact, Figure 32 shows that the same calibration parameters that lead to an optimal solution for one driving cycle (red line) are not extendible to different driving cycles (blue and green line). Consequently, it is necessary to repeat the calibration for the other driving cycles, with the same EF set created through DoE and the same principle of looking at the lowest value of $CO_{2_{ttw,eq}}$. Once recalculated the optimal EF pairs, here below the results for FTP 72 and JC 08 are shown in Figure 33 and 35:

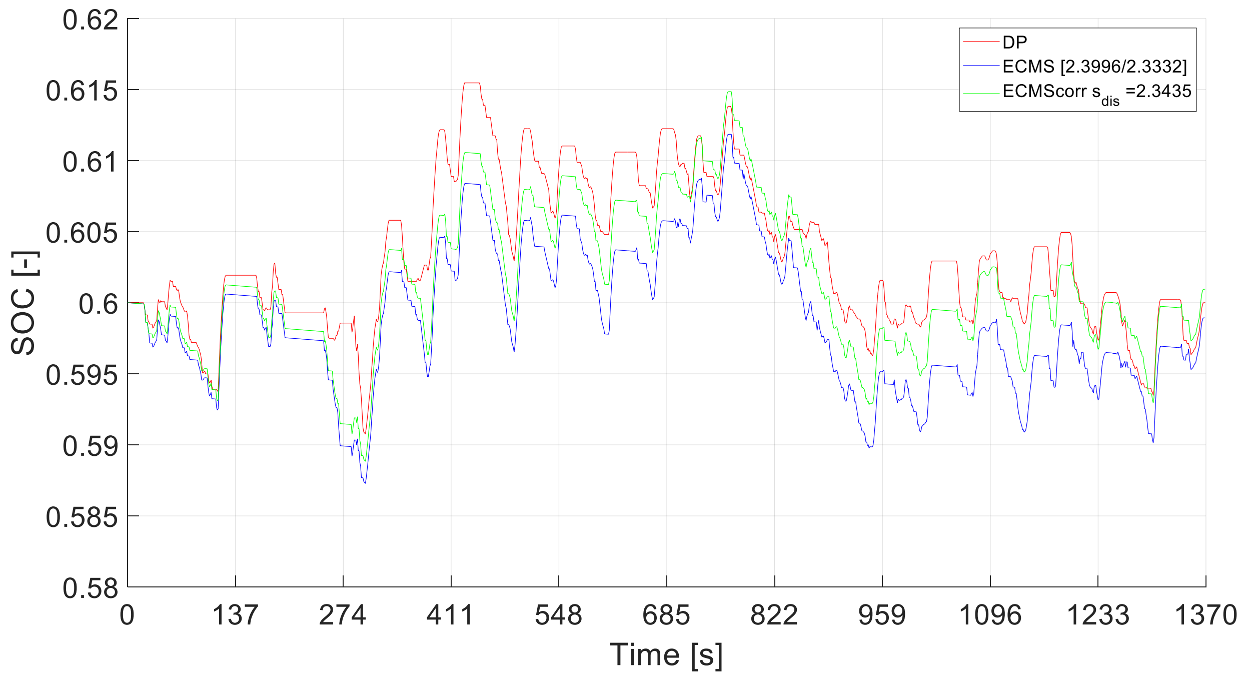

Figure 33- Comparison between correlated, uncorrelated EFs and DP for 4,5L on FTP 75 cycle

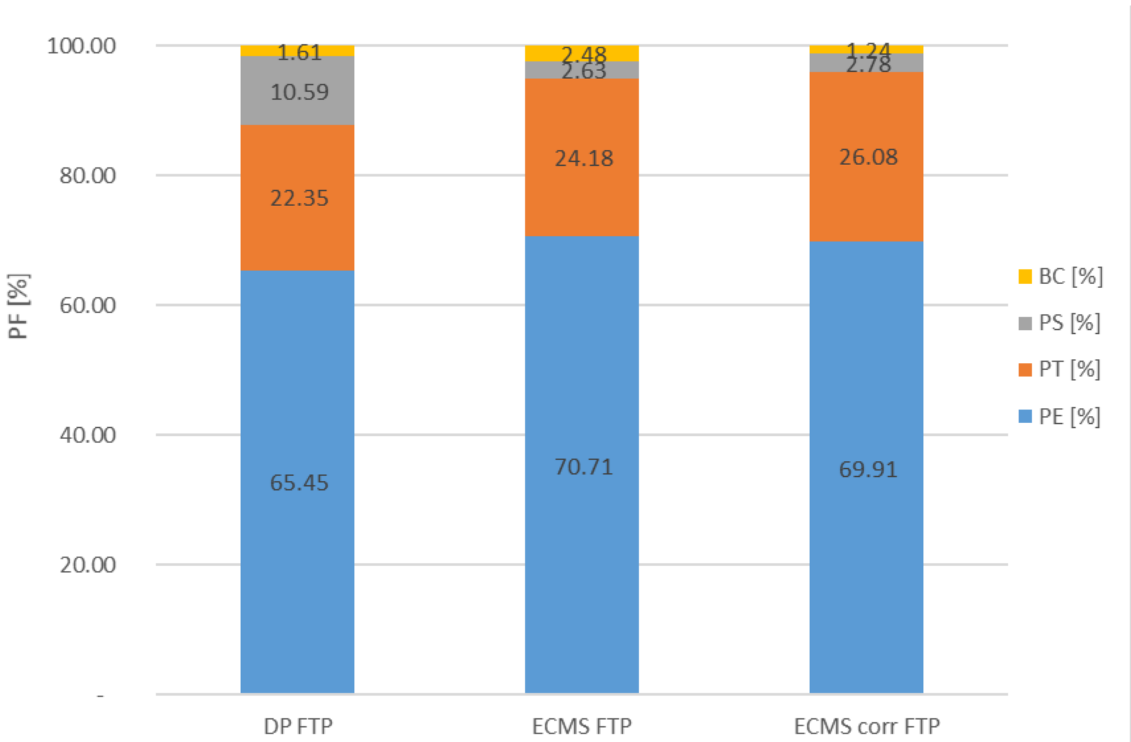

Figure 34- Detail on powerflow strategy for DP, ECMS and ECMS corr on 4,5L FTP75 cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	ΔCO2DP [%]	ΔCO2PT [%]
DP	\	\	332.25	332.25	0.600	0.591	0.616	0.000	0.00	-26.09
ECMS	2.3996	2.3332	332.53	333.35	0.599	0.587	0.612	-0.001	0.33	-25.75
ECMS corr	\	2.3435	333.25	333.25	0.601	0.589	0.615	0.001	0.30	-25.87

Table 9- Results for DP, ECMS and ECMS corr on 4,5L FTP 75 cycle

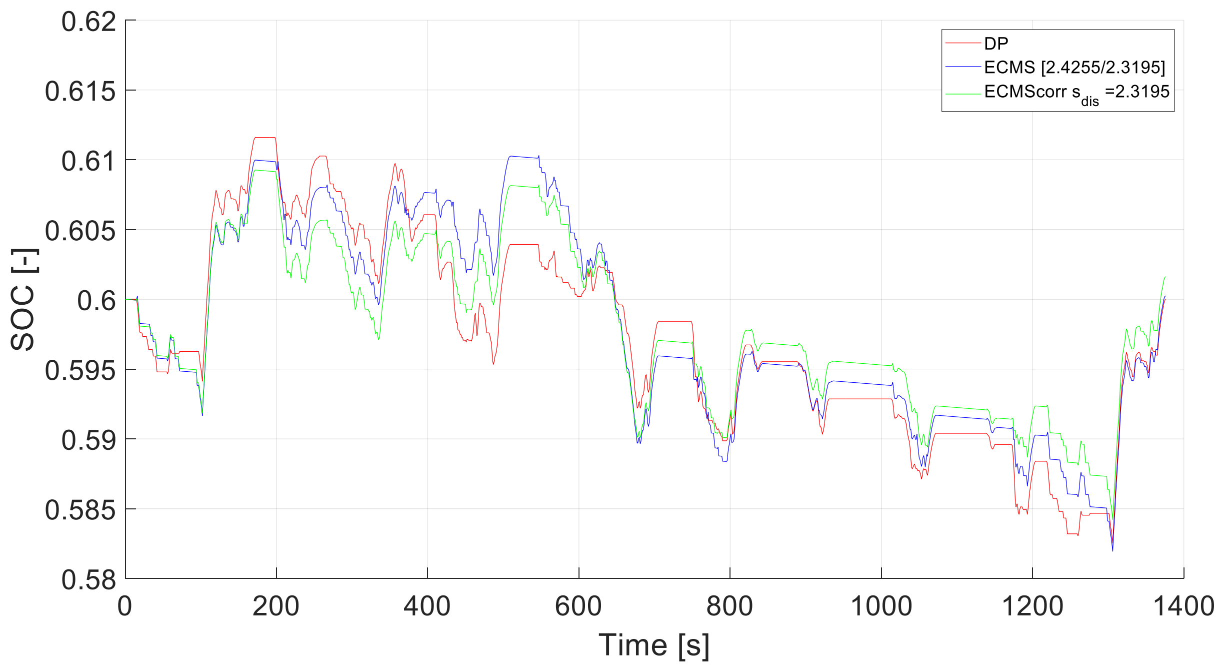

Figure 35- Comparison between correlated, uncorrelated EFs and DP for 4,5L on JC08 cycle

Figure 36- Detail on powerflow strategy for DP, ECMS and ECMS corr on 4,5L JC 08 cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	ΔCO2DP [%]	ΔCO2PT [%]
DP	\	\	327.33	327.33	0.600	0.583	0.612	0.000	0.00	-18.85
ECMS	2.4255	2.3073	329.64	329.64	0.600	0.582	0.610	0.0003	0.71	-18.28
ECMS corr	\	2.3195	329.50	329.50	0.602	0.584	0.609	0.002	0.66	-18.31

Table 10-Results for DP, ECMS and ECMS corr on 4,5L JC 08 cycle

Looking at the results above showed, ECMS controller still leads to good results in terms of CO_2 emission and SOC trend, leading to optimal results also on a more aggressive cycle (like FTP 75). Furthermore, comparing the CO_2 consumption results obtained with ECMS and correlated ECMS the latter provides generally best results, or comparable in the case of FTP 75. The SOC window, namely maximum and minimum SOC level reached through the mission are always lower for the correlated ECMS formulation and comparable with respect to DP. Also considering power flow through the cycle, correlated ECMS generally brings to better results, limiting the battery charging strategy with respect to the uncorrelated formula. Results obtained in this section allow to move uniquely to the correlated formulation as it is proved to bring to the best results in terms of the criteria shown on Chapter 5.3.3. Furtherly, this approach allows to strongly reduce calibration time and difficulty, as a unique calibration parameter namely s_{dis} is considered.

6. Internal Combustion Engine downsizing

6.1 Purpose

The idea behind HEVs is to compensate the low expertise of the thermal engine at some working conditions with an electric machine, that allows higher efficiency management. This idea can be pushed furtherly, considering an increase in use of the high-efficiency electric motor against the lower performances of thermal part, especially at lower regimes. The idea is to propose a reduction of the size of the ICE, to face these inefficiencies and furtherly reduce fuel wastes, considering that a smaller thermal part brings necessarily to lower emissions. In the automotive field, this procedure is commonly adopted and known as downsizing, that essentially consists in the reduction of the size of the Internal Combustion Engine with the extent to guarantee similar performances with a lower fuel cost, to comply with legislative standards. The common way to perform it is to reduce engine size while keeping the output power and torque almost constant by reducing the number of cylinders and adding a forced aspiration device such as charger or turbocharger or either by using techniques such as variable valve lift (VVL) and gasoline direct injection (DI) [10]. Downsizing leads to:

1. Reduced mechanical and thermal losses,
2. Lower engine weight and vehicle,
3. The engine operates in its optimum fuel consumption area.

1. and 2. are verified also for HEVs and 3. is especially true for full HEVs. In this section, engine downsizing is considered combined with the vehicle hybridization, in order to bring the reduction of the thermal engine to a higher extent and furtherly increase fuel economy, while providing sufficient power for propulsion. Considering that an additional electric part is present, it is not necessary to perform also a turbocharging system addition since the EM provides the sufficient torque and also, it is possible to reduce the thermal engine size substantially. Due to the additional value of engine size to be determined, now the problem becomes a multi-objective optimization procedure. In the following chapter, CI engine downsizing is proposed in the particular application of HEV. Results of a downsized 3L engine displacement with ECMS control will be shown alongside with a comparation with respect to the reference vehicle.

6.2 Results

Firstly, the correlated formula between the EFs has been proposed, in order to provide a further verification of the validity of the correlation, have been done, so another comparison test between the two strategies is proposed for the 3L downsized configuration.

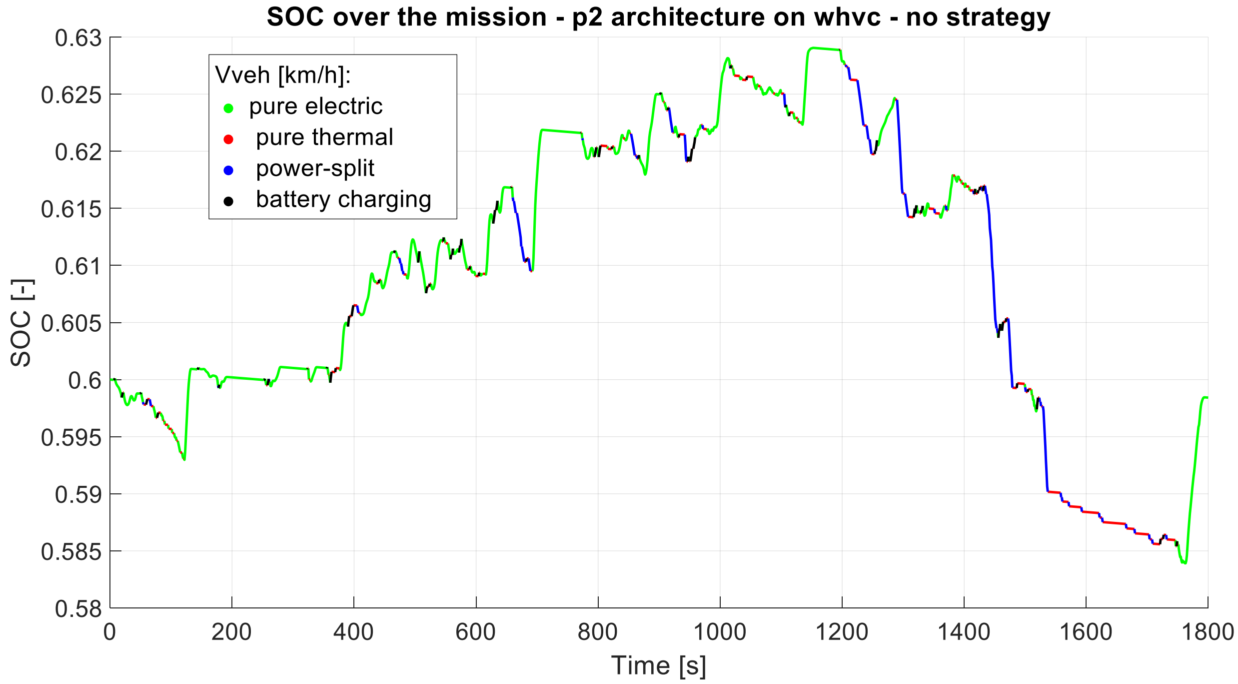

Figure 37-SOC level through the cycle, ECMS 3L on WHVC cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	PE [%]	PT [%]	PS [%]	BC [%]
ECMS	2.4826	2.3732	334.08	334.52	0.598	0.584	0.629	-0.002	53.72	33.11	7.61	5.55

Table 11-Results ECMS 3L on WHVC

Figure 38- SOC level through the cycle, ECMS corr 3L on WHVC cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	PE [%]	PT [%]	PS [%]	BC [%]
ECMS corr	\	2.4372	333.27	333.27	0.600	0.586	0.631	0.000	49.56	42.56	7.28	0.61

Table 12-Results correlated ECMS 3L on WHVC

By the results showed here above in Figure 37 and Figure 38, properly tuned ECMS control works and respects all the requirements for SOC and power requested. The results in terms of CO_2 emission are lower than the reference configuration with 4.5L, and the required power is always reached (there are no unfeasibilities). In particular, correlated ECMS leads to lower CO_2 consumption and a better power flow management with a reduced use of the battery charging and so the reduction of the calibration parameters by the use of the correlated formula is confirmed also for this case. In Figure 39, a comparison with DP and pure thermal results for the downsized 3L configuration in WHVC cycle is also shown:

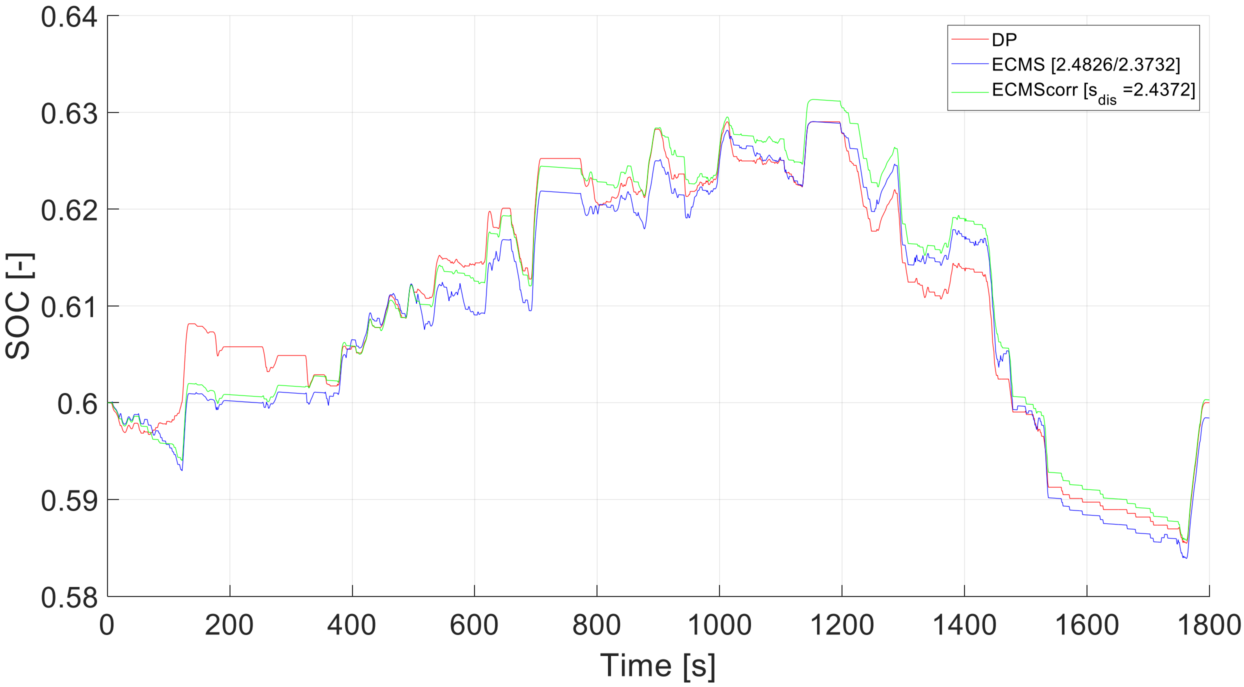

Figure 39- Comparison between correlated, uncorrelated EFs and DP for 3L on WHVC cycle

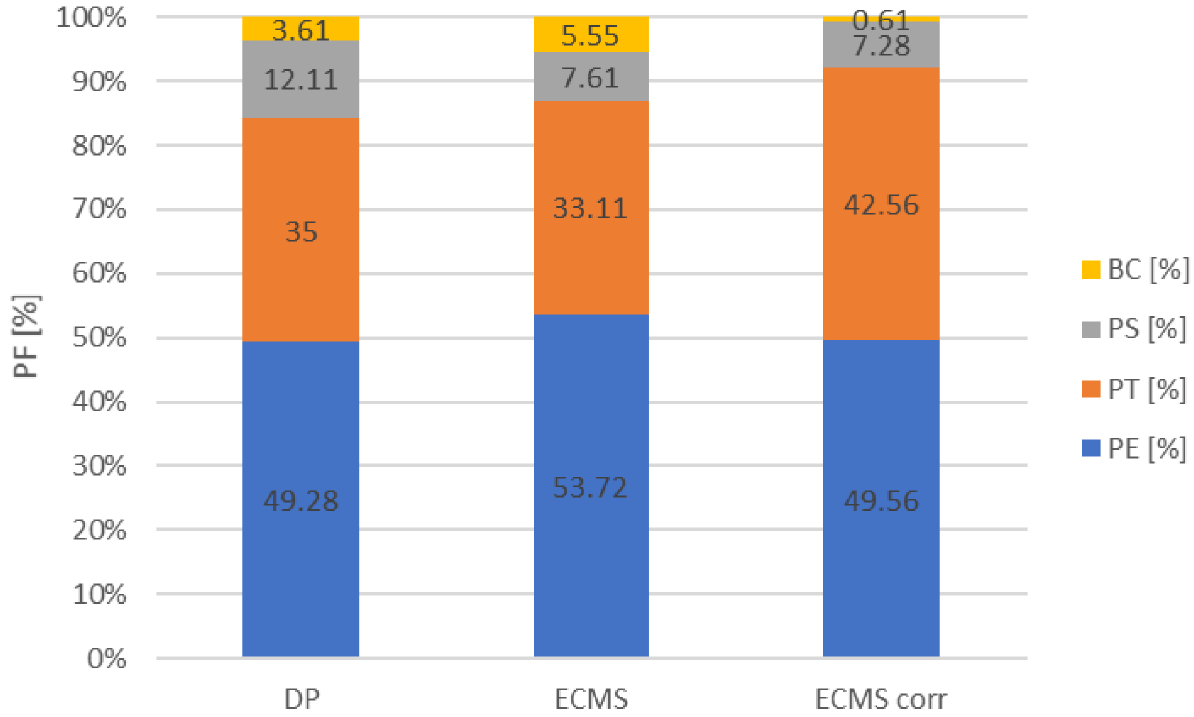

Figure 40- Detail on powerflow strategy for DP, ECMS and ECMS corr on 3L WHVC cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	ΔCO2DP [%]	ΔCO2PT [%]
DP	\	\	331.57	331.57	0.600	0.585	0.629	0.0000	0.00	-13.09
ECMS	2.4826	2.3732	334.08	334.52	0.598	0.584	0.629	-0.002	0.76	-12.42
ECMS corr	\	2.4372	333.27	333.27	0.600	0.586	0.631	0.000	0.51	-12.64

Table 13- Results for DP, ECMS and ECMS corr for 3L on WHVC cycle

Again, ECMS controller in its correlated formulation has provided a reduction of the CO_2 consumption up to -12.64% due to a reduced usage of battery charging with respect to the benchmark control strategy (DP). Furtherly, the downsizing of the thermal part led to a further reduction in consumption with respect to the pure ICE reference configuration on the same driving cycle of up to -15.23% (versus -12.64%).

Regarding the other driving cycles, the pure thermal configuration with a 3L ICE did not provide sufficient power for propulsion. On the other hand, by adding an electric machine, the hybrid powertrain was able to give sufficient torque to complete both FTP-75 as well as JC08:

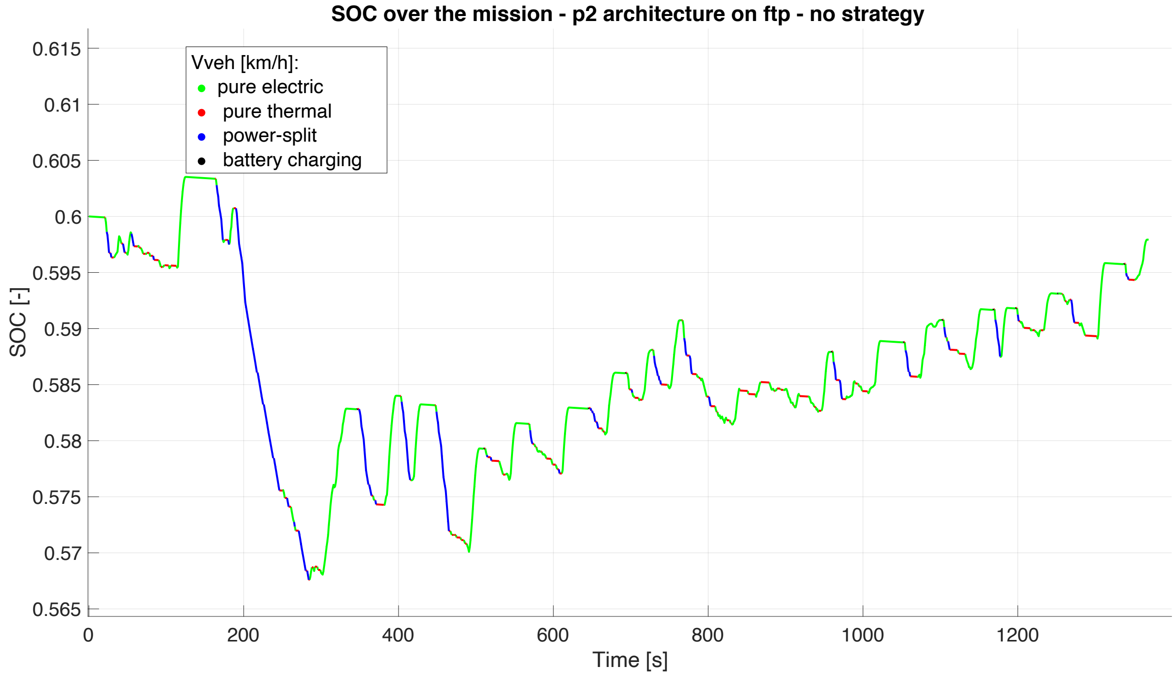

Figure 41-SOC level through the cycle ECMS corr on 3L FTP-75 cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	PE [%]	PT [%]	PS [%]	BC [%]
ECMS corr	\	2.4216	329.05	331.66	0.598	0.568	0.603	0.002	57.85	27.83	13.51	0.80
DP	\	\	331.13	331.13	0.600	0.573	0.602	0.000	56.90	19.94	18.99	4.16

Table 14-Results correlated ECMS, 3L FTP-75

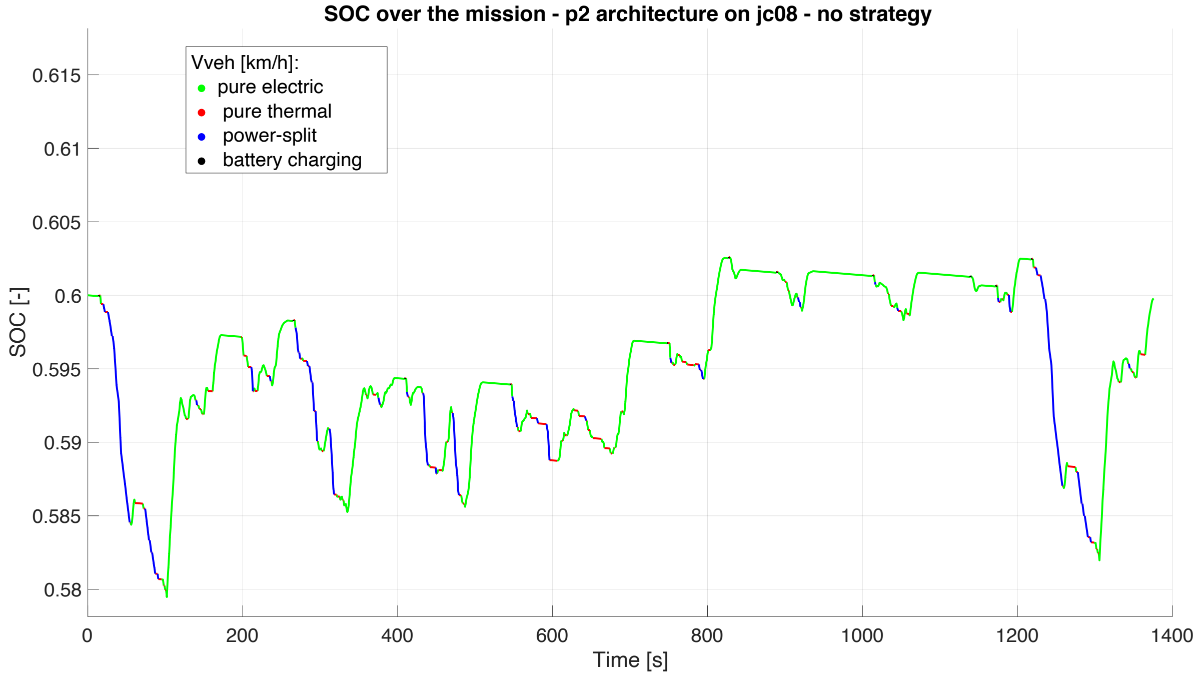

Figure 42- SOC level through the cycle ECMS corr on 3L JC08 cycle

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	SOCmin [-]	SOCmax [-]	ΔSOC [-]	PE [%]	PT [%]	PS [%]	BC [%]
ECMS corr	\	2.3776	326.10	326.58	0.600	0.579	0.603	0.002	66.72	21.88	10.61	0.80
DP	\	\	326.24	326.24	0.600	0.579	0.606	0	66.79	18.31	13.52	1.38

Table 15-Results correlated ECMS, 3L JC08

ECMS controller has provided to give good results in terms of SOC trend on both FTP-75 and JC08 cycle. As expected, there is a low usage of battery charging strategy especially with respect to DP controller in FTP (4.16% against 0.80%). SOC always reaches a value that is close to the reference one and this does not affect fuel consumption. A comparison between hybrid powertrain and pure thermal is not feasible but, the emissions results obtained by ECMS controller are very similar to the benchmark strategy ones with only a 0.1% difference. Consequently, ECMS brings to the expected reduction in fuel consumption due to the hybridization of the powertrain, as expected. The results of the engine downsizing are here summarized:

Driving cycle	CO2ttw PT 4,5L [g/km]	CO2ttw,eq HEV 3L ECMS [g/km]	CO2 reduction [%]
WHVC	393.55	333.27	-15.32
FTP-75	449.54	331.66	-26.22
JC08	403.36	326.58	-19.04

Table 16-Resuming results for engine downsizing

As can be seen from Table 16, the hybrid downsized powertrain brings out a substantial reduction of CO_2 consumption for all the cycles tested, ranging from a 15% to a 26% reduction on WHVC and FTP-75, relatively.

7. A-ECMS

The ECMS has proven to bring to good results, with the downside of the need to calibre EFs accurately, procedure that has to be done for each driving cycle and makes the algorithm not prone to adapt to various driving scenarios. When cycle is not known a priori, it is more difficult to find the proper values of s_{chg} and s_{dis}. In fact, the calibration parameters can't be kept constant if different missions are reached: in this case, the solution can't be considered as optimal or would not lead to the charge sustainability condition, as can be seen on Figure 43. An adaptive supervisory controller is necessary, that allows the calibration parameters to change through the cycle. That's the idea behind the Adaptive-ECMS or A-ECMS, in which the EF are not kept constant through the cycle but change, according to a law in time, depending on the chosen parameters.

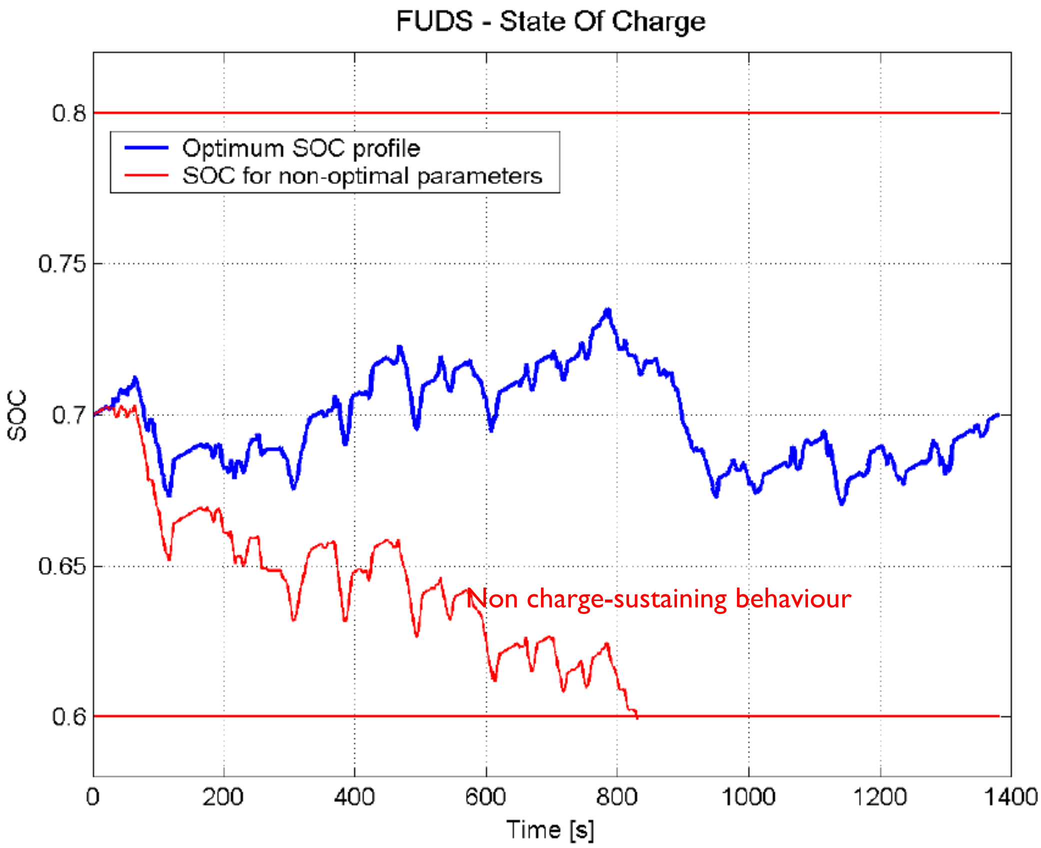

Figure 43-Effect of non optimal parameters on the SOC trend for ECMS control [3]

The adaptivity can be done in different ways, in literature today are present [4]:

- Adaptivity based on driving style prediction,
- Adaptivity based on driving pattern recognition,
- Adaptivity based on driving cycle prediction,
- Adaptivity based on SOC of the rechargeable system.

Any type of controller is conceived to be executed online with low calibration times, with the downside that the values of consumption obtained by ECMS can't be reached but still, an optimal solution with respect to the other controllers can be achieved.

7.1 A-ECMS strategies

7.1.1 Adaptivity based on driving style prediction

Research has found that driving style strongly affects energy management problem in HEVs, and the adaptation of the EFs can be done basing on the information over the way the driver uses the throttle and the brakes. For these controllers, the actual data for velocity and acceleration are converted into driving style categories [11]: aggressive, conservative and moderate. Former category is generally characterized by strong accelerations and brakes, whereas the last is more related to less changes in the throttle position. Some offline tests in order to precisely determine the characteristics of the cluster have to be done through driving simulators. At each phase of the driving mission, a hybrid algorithm based on K nearest neighbor and expectation maximization methods, are designed to recognize the driver's driving style according to different features such as acceleration and braking points. A driving style is assigned and used in order to determine, at each step, the equivalence factor as follows:

$$s(t) = s_0 + \psi \cdot (s - s_0) \tag{7.1}$$

7.1.2 Adaptivity based on driving pattern recognition

The data on the acceleration and velocity, can also be collected to identify a precise driving pattern similar to the driving conditions such as urban, suburban, motorway. More parameters are now needed, such as velocity, acceleration, average speed, stop total time. At each time step, the information is used to identify which pattern the vehicle is undergoing, and for each pattern a precise optimal EF set is assigned, that are pre-computed and stored in the memory of the controller.

7.1.2 Adaptivity based on driving cycle prediction

This type of controller is based on EF adaptivity on the vehicle speed through the cycle. An instantaneous adaptation can be done as follows:

$$s(t) = s_0 + K_v(v(t) - v(t-1)) \tag{7.2}$$

With K_v representing the proportion gain of the EFs on the velocity, a parameter that have to be properly tuned. This type of controller provides a continuous adaptation, so that at each time instant the EFs change. Due to the difficulty of the calibration of the proportional gain and the big variations in velocity that make the controller very responsive, it has generally the need to be associated to a limitation of the EFs, that is generally done in the interval [2,3] for the common driving scenarios.

Adaptivity can also be managed by using a velocity forecast ability [5]: a neural network-based velocity predictor is constructed to forecast the short-term future driving behaviors by learning from history data. Then the velocity predictor is combined with adaptive-ECMS to provide temporary driving information for real-time EF adaptation. With driving simulations, the controller recognizes the driving behaviors from the sample driving profiles and the velocity predictor is able to forecast the future velocity with acceptable errors.

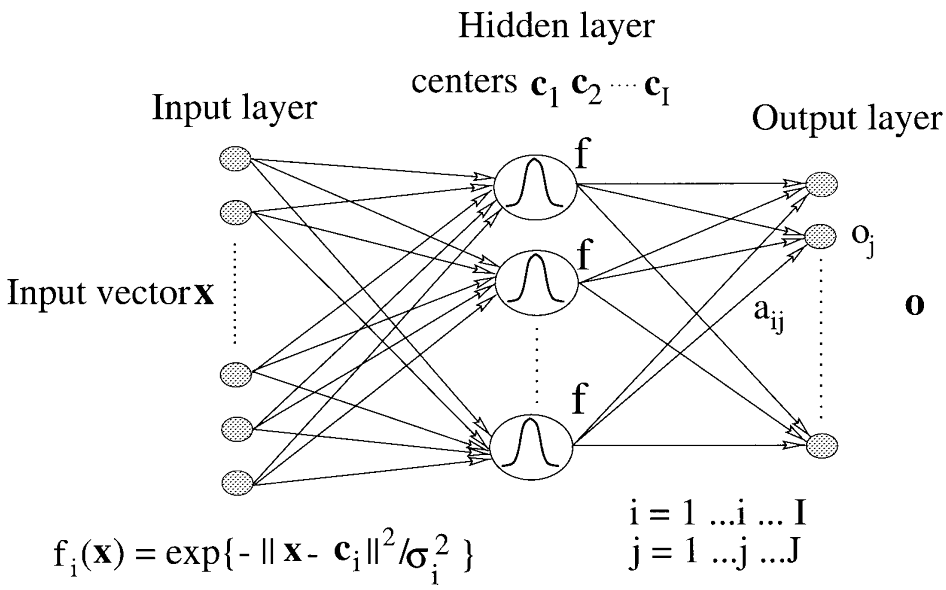

Figure 44-Radial basis function scheme

A scheme of the radial basis function is shown on Figure 44, in which radial basis function *f* are defined as activation function, namely they define an output of a node, given an input or a set of inputs, creating an output layer. The intermediate or hidden layer has a non-linear radial basis function activation, whereas the output is a linear function. Speed forecasting time strongly affects the performance of this kind of A-ECMS: it can vary from seconds to minutes, a higher forecast time can increase the accuracy of the A-ECMS controller and reduce emissions, but an higher time can lead to higher errors, as can be seen on Figure 45. Still, an offline training is needed, after collecting a proper number of driving cycles.

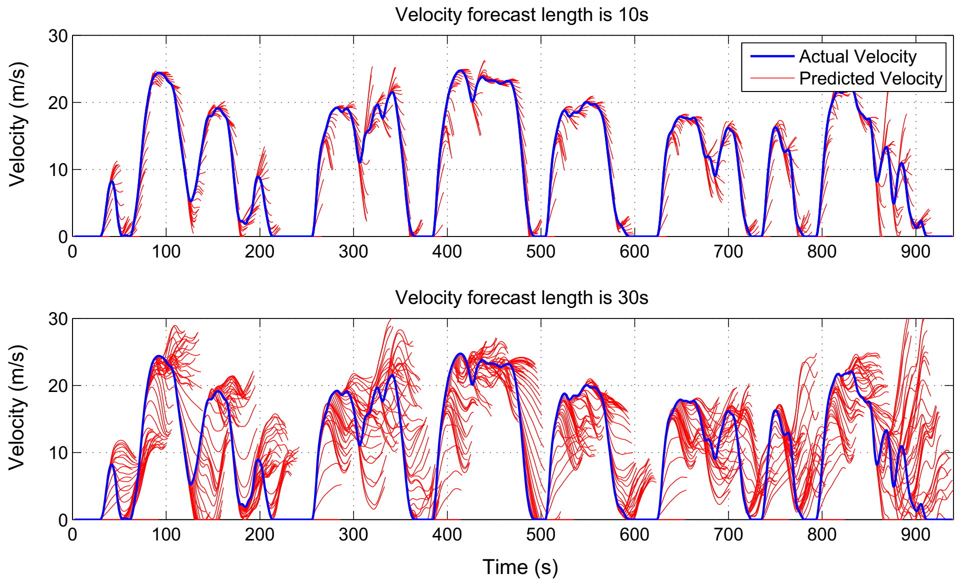

Figure 45-Velocity forecast ability based on RBN [5]

7.1.3 Adaptivity based on SOC

A valid alternative to determine the change of the co-state variables in time, is to address it to the change in the SOC of the battery. In this way, a proper trend is guaranteed for the EFs, that can vary according to the instantaneous value of the battery charge. In this way strong SOC variations can be kept under control and guarantee the charge sustaining condition. The further advantage, is that this kind of method can be easily implemented onboard and robust, relying only on feedback from the battery. Among these controllers, two type can be defined:

- Continuous A-ECMS, in which the variation of the EFs is done each T seconds,
- Discrete A-ECMS, in which a continuous variation of EFs is guaranteed.

These adaptation laws are based on a proportional integrative controller (PI controller).

7.1.3.1 Continuous A-ECMS

The adaptation uses the target value of SOC, namely the initial SOC level as the reference, and calculates at each time step the EFs as follows:

$$s(t) = s_0 + k_P\left(SOC_{target} - SOC(t)\right) + k_I \int_0^t \left(SOC_{target} - SOC(t)\right) d\tau \qquad (7.3)$$

Where k_P and k_I representing the proportional and integral contributions of the adaptation law. In this case, an integrative contribution is associated with a proportional one to provide more accuracy in the case that a constant value has to be tracked. There are, nonetheless, two additional parameters to be calibrated. This strict SOC follow-up can lead sometimes to undesired solution and a too severe correction when the SOC goes over the reference value.

Proportional and integral coefficients have to be tuned, considered that an increase of the parameters leads to a charge sustaining behaviour, but a huge increment of especially the integral coefficient leads to instabilities, as can be seen in Figure 46:

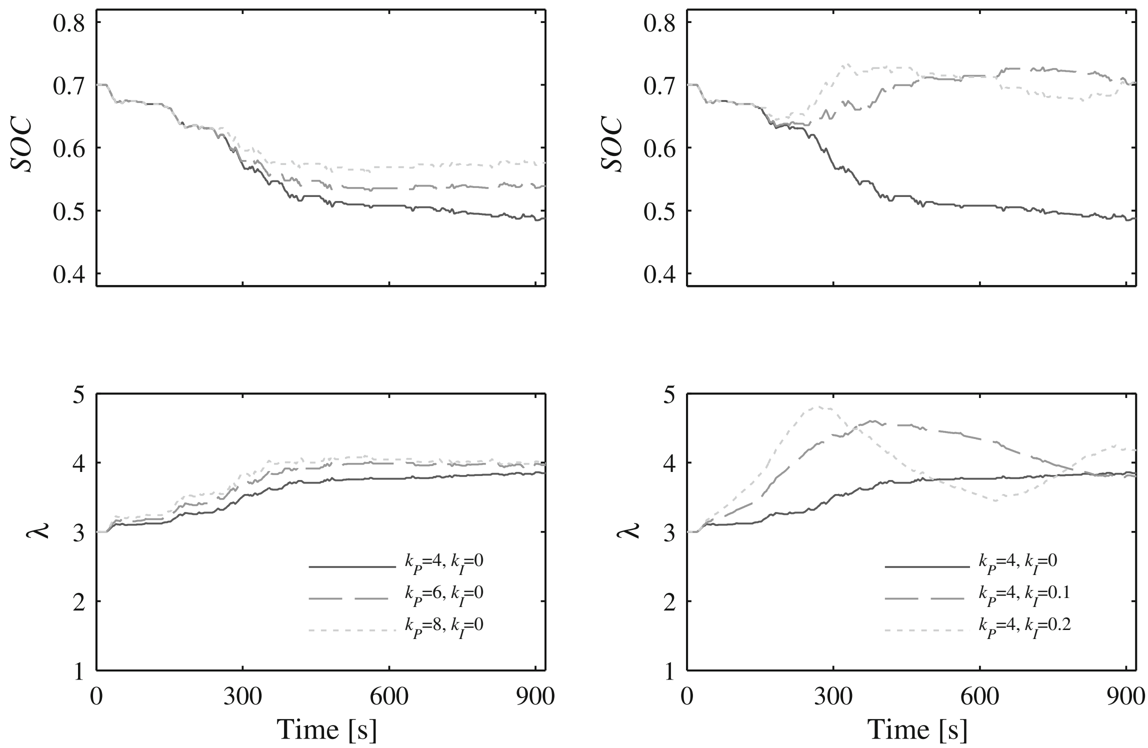

Figure 46-Influence of the proportional and integral coefficients in the continuous A-ECMS [4]

Continuous A-ECMS is characterized by good accuracy but a higher computational effort is required with respect to the discrete formulation and can lead to a quasi-constant SOC trend with an increase in fuel consumption.

7.1.3.2 Discrete A-ECMS

Discrete A-ECMS corrects the SOC of the battery at a defined time interval T, allowing the battery to go through different SOC states, still limited to the upper and lower limits. This leads to a less responsive approach that furtherly moves toward a reduction of fuel wastes, preserving the durability of the battery in time. Discrete formulation provides that the formula is applied each T seconds:

$$s(t) = \frac{s(t-T)+s(t-T-1)}{2} + k_P^d\left(SOC_{target} - SOC(t)\right) \tag{7.4}$$

In 7.4, a stabilization of the EFs is guaranteed with a bisection formula, based on the auto regressive moving average (ARMA) model. This formula imposes charge sustainability condition periodically in a discrete time interval, that has to be chosen depending on battery characteristics and has to be suitably chosen alongside with the proportional coefficient k_P.

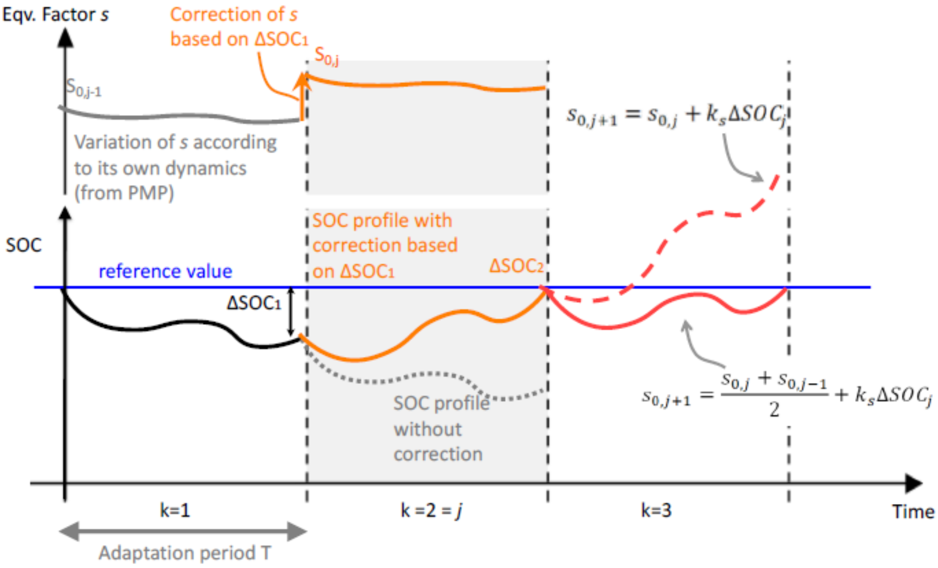

Figure 47-Effect of the Discrete A-ECMS on the EF and SOC variation through time [11]

As can be seen in Figure 47, the periodic formula allows to update the EFs periodically and this has a strong influence on the SOC profile over the cycle. It is also possible to notice that in the second part ($k = 2$) the absence of correction would lead to a charge depleting trend. Furthermore, in the last part (for $k = 3$) the bisection formula allows to stabilize the SOC level and not undesirably exceed the upper bound.

Still, as the continuous A-ECMS formulation two calibration parameters have to be properly chosen. Generally, a higher reset time T leads to a charge depleting trend, whereas a high proportional gain leads to a charge sustaining trend, as the continuous formulation. This can be seen on Figure 48:

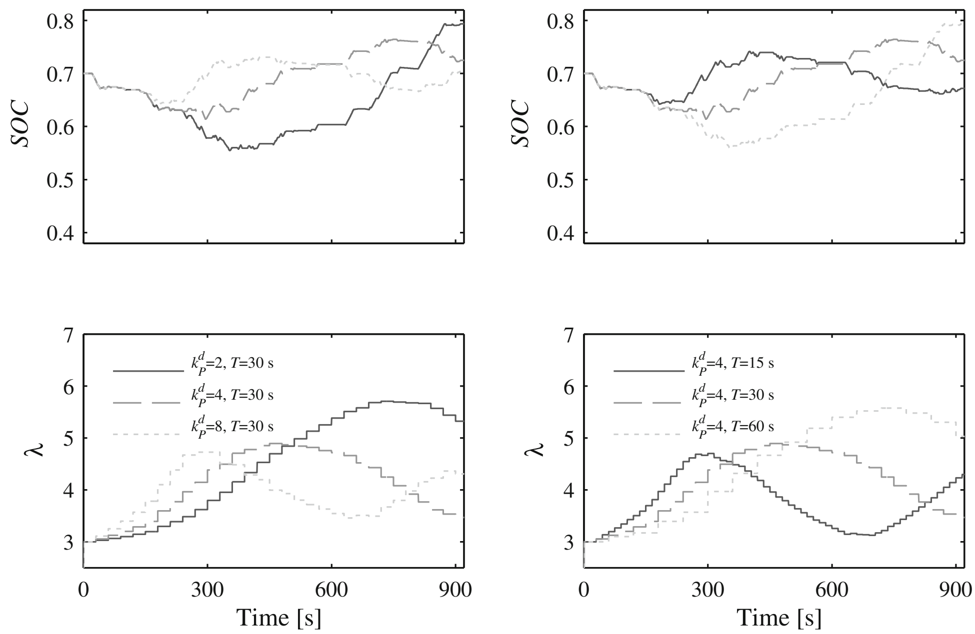

Figure 48-Influence of proportional gain and reset time on the discrete A-ECMS [4]

A comparison between continuous and discrete A-ECMS is shown on Figure 47:

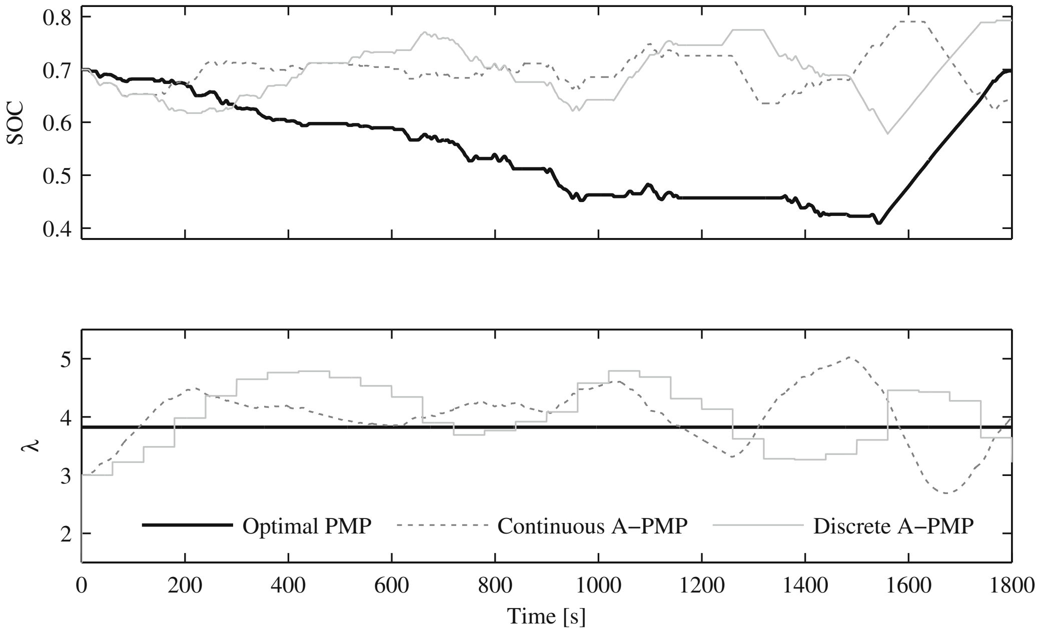

Figure 49-Comparison between continuous and discrete A-ECMS

It is possible to notice that the discrete adaptation changes the value of the co-state variable each 60 seconds, whereas the continuous adaptation constantly changes the value. Furtherly, Periodic adaptation provides a lower oscillation of the calibration parameter and also a less SOC sensitive control.

8. Conclusions

8.1 Summary

The aim of this work was to provide a strong and implementable onboard HEVs control strategy, to manage the power-flow or the energy management problem between the electric machine and the thermal part on different driving cycles. A control strategy called Equivalent Consumption Minimization Strategy (ECMS) control was proposed and tested in a MATLAB optimization tool on a full hybrid heavy-duty vehicle with a 4,5L compression ignition engine, proposing a comparison with a benchmark control strategy (DP) on the same configuration. A way to rapidly calibrate the tuning parameters in ECMS, called Equivalence Factors was shown and has proven to give the optimal pair of control parameters, assigned a driving cycle, by means of a parameter called equivalent emission, or $CO_{2eq,ttw}$. This criterion was applied in different driving cycles and has always given the optimal solution in all the cases. Once a basic ECMS formulation was implemented, a penalty function in order to furtherly limit the SOC operational range was proposed and tested. Then, ECMS application on different driving cycles is proposed (WHVC, FTP-75, JC08) and the results are compared with the benchmark control strategy and a pure thermal layout with the same thermal engine size. A correlated formula for the EF definition has been proven to always give the most optimal results, in terms of decrease of fuel wastes and SOC level requirements through the cycle. This has guaranteed a reduction of the calibration parameters and, consequently, calibration time. ECMS has proven to have a reduced calculation time with respect to other strategies and has proven a reduction in CO_2 consumption with values ranging from 13% to 26% with respect to pure thermal, depending on the driving cycles considered, amidst a slightly worse but comparable result with respect to DP. An engine downsizing of the reference configuration, combined with the hybrid powertrain is advanced and tested, leading to a reduction in CO_2 emissions with respect to the reference pure thermal 4,5L powertrain of 15,3% in the WHVC cycle and 26,3% in FTP cycle. A brief overview of the different types of Adaptive-ECMS was shown in the last part, with a particular focus over the adaptivity based on the SOC of the battery. Table 17 provides a resume for all the results obtained:

Control Strategy	s_chg[-]	s_dis[-]	CO2ttw [g/km]	CO2ttw,eq [g/km]	SOCfinal [-]	ΔCO2PT ref 4,5L [%]
DP 4,5L WHVC	\	\	337.86	337.86	0.600	-14.15
ECMS 4,5L WHVC	\	2.4172	338.26	338.60	0.599	-13.94
DP 4,5L FTP-75	\	\	332.25	332.25	0.600	-26.09
ECMS 4,5L FTP-75	\	2.3435	333.25	333.25	0.601	-25.87
DP 4,5L JC08	\	\	327.33	327.33	0.600	-18.85
ECMS 4,5L JC08	\	2.3195	329.50	329.50	0.602	-18.31
DP 3L WHVC	\	\	331.57	331.57	0.600	-15.75
ECMS 3L WHVC	\	2.4372	333.27	333.27	0.600	-15.62
DP 3L FTP-75	\	\	331.13	331.13	0.600	-26.34
ECMS 3L FTP-75	\	2.4216	329.05	331.66	0.598	-26.22
DP 3L JC08	\	\	326.24	326.24	0.600	-19.12
ECMS 3L JC08	\	2.3776	326.10	326.58	0.600	-19.04

Table 17-Resuming table for the results obtained

8.2 Future outlook

This study was uniquely a first step towards a reliable and on-line implementable algorithm for HEVs control, that can reduce fuel consumption. Some next steps should be done in order to make the algorithm computationally lighter and appliable to every driving scenario. In this sense, it would be crucial to implement the adaptive ECMS formulation the MATLAB optimization tool and furtherly analyze and test all the formulas present in literature, shown in Chapter 7. Also, it would be interesting to implement an algorithm to define a precise EF set that automatically tunes according to different driving conditions, depending on forecast speed of the vehicle, acceleration, driving style recognition or based traffic information.

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