POLITECNICO DI TORINO

Master Degree Thesis in Mechatronic Engineering

Optimization of the control logic of a hybrid electric vehicle exploiting ADAS information

Supervisor

Prof. Angelo Bonfitto

Co-Supervisors

Prof. Andrea Tonoli

Prof. Nicola Amati

PhD Candidate Stefano Favelli

PhD Candidate Eugenio Tramacere

Candidate

Giulia Cilio

Academic Year 2022-2023

Acknowledgements

To my family, for always supporting me, with an advice or with a hug. To always be happy with my successes.

To my mum for always looking for the best advice to give me, keeping me serene despite everything, and encouraging me through difficult choices providing me with unfailing support.
To my dad for the kind words in the bad moments, to have always embraced my choices over the years.
To my sister for always being by my side even if from afar.
I hope you'll be proud of me.

To Mario who taught me to live lightly and to find the bright side of things. To always be near even when I was stressed and overwhelmed, continually encouraging me.

To Sabina with which I used to vent in the evening coming home.

To all my friends for the laughs and the nights you hoped would never end.

To my supervisors, Prof Angelo Bonfitto, Prof Andrea Tonoli and Prof. Nicola Amati for giving me the possibility to work on this interesting project.

To Luca, Stefano and Eugenio for always being there when I needed help during the thesis work.

To all of you I say thank you.

Abstract

CO2 emissions, causing global warming of the earth's atmosphere, is one of the main concern of the past and present years. Reduction of emissions becomes the main focus of many researches concerning, in particular, the automotive world. This is one of the reasons why electric and hybrid vehicles, together with autonomous systems, have been introduced in the new generation, not only to guarantee more comfort to human users but chiefly as a way to reduce gas emissions.

The aim of this project regards the minimization of vehicle 's pollutant emissions and fuel consumption integrating Advanced Driver Assistance Systems (ADAS) to the control logic and having in this way a more ECO-oriented control strategy. The vehicle, case of study of this thesis, is a 48V mild-hybrid (IVECO Daily) characterized by a P1 configuration.
The proposed strategy for emissions reduction has been developed in MATLAB/ Simulink environment and verified through simulations over European standard driving cycles for test procedure. The work focuses on the definition of a space-time horizon which allows us to have a driver's demand prediction to be sent to the ECMS (Equivalent Consumption Minimization Strategy) algorithm responsible for power splitting management, this is done integrating an adaptive cruise control logic, based on radar and camera, to the vehicle model. The knowledge of the driving cycle in advance makes it possible to have a real implementable strategy.
During testing phase, a big reduction in fuel consumption and CO2 emissions has been observed in the analysis of both the urban part and the extra-urban part of a WLTC cycle with respect to the standard baseline of the vehicle model, which does not take in consideration any ADAS information. Afterwards, the same control strategy used for the analysis of the two sections of the drive cycle has been used over the entire cycle where an overall improvement can be observed.

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Chapter 1

Introduction

1.1 Background

Nowadays, minimization of global pollutants, has become one of the most important challenge in the automotive industry. Passenger cars are a major polluter, accounting for 61% of total CO_2 emissions from EU road transport [1]. The EU says:

> "it is an ambitious contributor to global efforts to fight climate change and reduce greenhouse gas emissions, which are caused by human activity".

In 2022, EU economy greenhouse gas emissions totalled a 3% more of CO_2 compared with 2021. In order to reduce the CO_2 emissions governments are setting ambitious targets that road vehicles should follow to avoid emissions in the early future, imposing restrictions in terms of emissions on each registered vehicle. A possibility of CO_2 emissions reduction is given either by electrification of the vehicles or by making vehicles more efficient, which in the case of this thesis leads to the use of automation systems.

1.1.1 Electrification

At this time, one of the biggest trends in the automotive industry concerns vehicles electrification. Electrification is the process by which it is possible to replace vehicle components that operate on a conventional energy source powering instead the vehicle by electricity. Electrical systems can be monitored, which means they can be optimized and controlled, being so more efficient than others. The process of electrification holds great potential to reduce energy demand and so fuel consumption because of the efficiency of electric technologies which is generally much higher than fuel-based alternatives with similar energy services. In 2021, most CO_2 emissions reduction, related to electrification, can be found in the road transport sector, especially within the light-duty vehicle segments [2]. In 2019, total plug-in electric cars captured 2.5% of the global car market, that's a 400% increase from 2015. Battery electric vehicles (BEVs), instead, accounted for 74% of the 2019 sales and by 2025 it is expected there will be more than 400 electric vehicle models available globally [3]. In the last decade, petrol and diesel engines have became hybrid, plug-in hybrid and fully electric powertrains. Hybrid vehicles posses the ability to collect electrical energy during deceleration and then add torque under acceleration leading to a significant reduction in CO2 emissions and using bigger batteries or increasing the power of the motor they can extend their operating window providing further small improvements. As stated in [3], self-charging hybrids can improve their CO2 emissions to meet current 2030 European targets.

1.1.2 Automation

Automation introduces systems able to assist humans in driving, with automated vehicles some aspects of a safety-critical control function occur without direct driver input. It is possible to distinguish between partial automation, providing partial assistance to drivers in the form of cruise control, automated braking and other safety features, designed to warn you if you are at risk, and high automation, often referred to as driver-less with the potential for improvement of transportation system, road safety and environmental health.
Apart from safety opportunities, vehicle automation can also have a big advantage in environmental, changing for example the need for individualized parking spaces or lessening wrong driving behaviour, resulting in further reductions of air pollutants. Nowadays, full automation is not still available but we can find some advanced driver assistance systems in the automotive market which provide lower levels of automation able to assist a driver in case of imminent dangers. The more the autonomous capabilities of the vehicles increase, the more the efficiency improvements we can see, for example, introducing features such as adaptive cruise control or highway platoon driving which can be a good option for fuel saving.
Currently, it is possible to find self-driving vehicles only in limited and designated locations and conditions. Autonomous vehicles, as well as other vehicles with no automated driving features, need to be tested before they can be approved, companies must comply with Federal Motor Vehicle Safety Standards (FMVSS) and certify that their vehicles are safe.

1.2 Project overview

This thesis work is part of a bigger research project funded by the Piedmont region through the "Pi.Te.F." (Piattaforma Tecnologica di Filiera) [4] in collaboration with Politecnico di Torino [5], Dayco Europe S.r.l. [6], Podium Advanced Technologies [7] and others.
The project in question is called AutoECO project and aims at developing a P1 hybrid vehicle (Light Duty Vehicle) equipped with ADAS (Advanced Driving Assistance Systems) sensors and a high-level control logic able to minimize fuel consumption and gas emissions.
In particular, the purpose of this thesis is:

- Hybridise the vehicle's powertrain so to have an electric motor combined with a combustion engine in a P1 configuration, according to the European standards;
- Create a high-level control logic that can be combined with the information comeing from an ADAS sensors perception of the surrounding environment;
- Improve the efficiency of the ADAS logic to obtain a reduction of CO2 emissions. emissions;

1.3 Thesis outline

This thesis is organized into six chapters:

The first chapter (Introduction) gives an overview of the project, identifying the reasons why the project was carried out and giving some ideas of the possible solutions to a general problem.

The second chapter (Theoretical background) gives an overview about hybrid vehicles and related technologies. This chapter contains a detailed classification of hybrid electric vehicles together with the description of different energy management control strategies. Autonomous vehicles and several Advanced Driver Assistance Systems are also introduced.

The third chapter (Vehicle model), includes the structural description of the schematic model of the vehicle. Here it is possible to find the vehicle parameters, the model approach and the description of each component that has been used for the development of the model in the MATLAB/Simulink platform.

The fourth chapter (Control strategy) describes the different types of controllers solutions originated from the research work. Three different control logic are described for three different situations: controller for internal combustion engine only (non-hybrid vehicle), controller for hybridized vehicle model, controller for a hybridized vehicle model which takes in consideration ADAS information.

The fifth chapter (Simulations and results) collects all the work results explained through the use of figures and tables.

Finally, the last chapter is dedicated to the conclusion which briefly restate the main points of the project with a digression on the possible future developments.

Chapter 2

Theoretical background

2.1 Hybrid electric vehicles

The main characteristic of a hybrid electric vehicle (HEV) is the use of two different sources of energy: the Internal Combustion Engine (ICE) and the electric motor/-generator (EMG).
Through the use of these two propulsion systems it is possible to reduce the environmental pollution solving the problem of short driving distance of electric vehicles (EVs) caused by the low energy density of a power battery. Moreover, in hybrid electric vehicles, the ICE is able to work close to its maximum efficiency working points and, since less power is required, it is also possible to reduce the combustion engine size without compromising the overall performance.
Some of the benefits offered by hybridization are the possibility to use the rechargeable energy storage system (RESS) for regenerative braking and as an energy buffer and to shut down the engine when it is not needed (Start and Stop feature).

2.2 HEVs Classification

In hybrid electric vehicles, the electric motor is more efficient at producing torque, for example, while the combustion engine is better for maintaining high speed. This is the reason why different configurations of HEVs have different conditions and so different control strategies in order to acheive the optimization of the efficiency of both the engine and motor performances. Improved efficiency and lower emissions are some of the primary benefits of hybridization. HEVs can be classified depending on the size of the electric powertrain, the topology and the position of the electric motor.

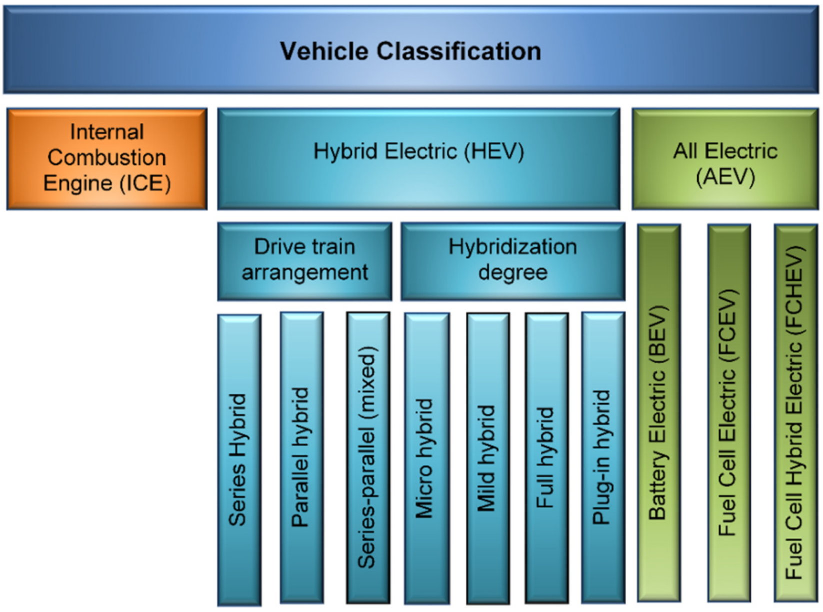


Figure 2.1: HEVs classification

2.2.1 HEVs classification based on topology

The topology of the HEVs architecture depends on the connection between the ICE and the electric motor. Hybrid drivetrain can be classified as series, parallel and series/parallel. For series configuration, the engine charges the battery and the battery charges the electric motor which powers the vehicle, while for parallel configuration, both engine and electric motor are used for propulsion of the vehicle.

- **Series configuration**

  In series configuration (Figure 2.2 [8]), a generator is connected in series with an ICE, mechanical energy is converted into electrical energy and transmitted to the electric motor which converts again the electrical power into mechanical one to drive the wheels. The energy from the ICE is converted twice, (mechanical to electrical, electrical to mechanical) thus leading to the presence of losses.
  The main function of the ICE in this case is to generate electricity for the battery which feeds power to the traction motor. A big advantage in the series configuration is the high efficiency of the ICE since it is decoupled from the wheels. Internal combustion engines in series configurations are usually small and they are seen as secondary source for the vehicle, being powered mainly

by the electric motor.

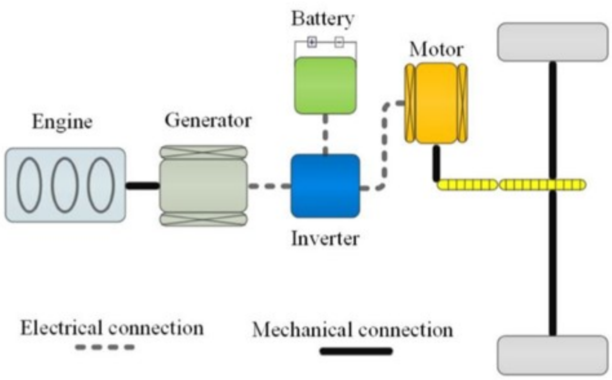


Figure 2.2: Series configuration

- **Parallel configuration**
  Engine and electric motor can work independently or together to provide traction. The two sources of energy are connected with a belt, a gear set or a chain, power from the ICE and from the electric motor are summed together and then sent to the wheels. The electric motor, in the parallel configuration (Figure 2.3 [8]), is usually smaller and less powerful with respect to the one in the series configuration, while the engine is bigger and has the possibility to send energy to the wheels in a direct way.
  With the parallel configuration we can avoid two energy conversions, in this case the drawback is related to the optimal torque split between ICE and EM.

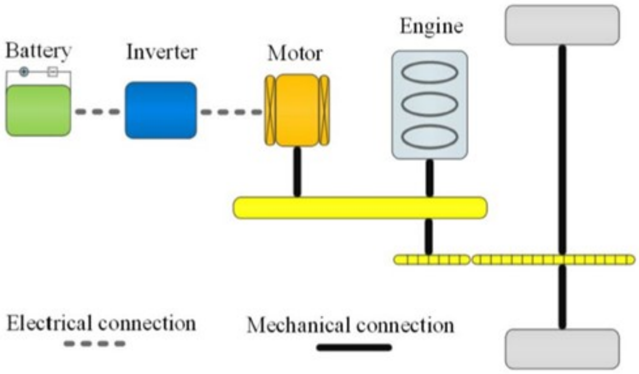


Figure 2.3: Parallel configuration

- **Series/Parallel configuration**
  The use of clutches to engage/disengage the different sources of energy makes this configuration more flexible with respect to the others. This is mostly a parallel hybrid, but it contains some features of a series hybrid, it takes the advantages of both series and parallel configurations (Figure 2.4 [8]).

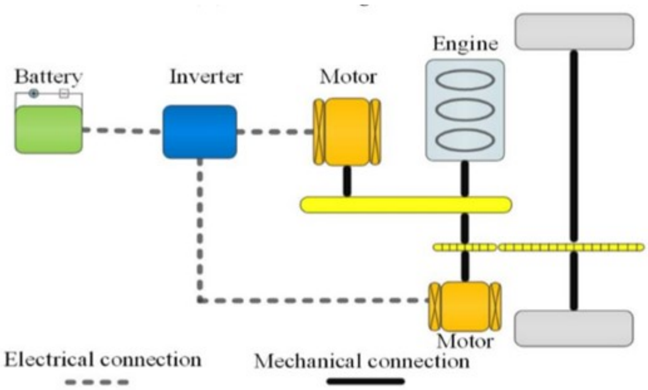


Figure 2.4: Series/Parallel configuration

2.2.2 Position of the electric motor

A further classification can be done analysing the position of the secondary energy source with respect to the ICE.

- **P0:** The electric machine is directly connected to the engine, positioned on the front, so that ICE and electric machine have the same angular speed and there is no possibility of mechanical disconnection between them. In this configuration power and torque are limited due to the restricted space for the installation. The P0 architecture, such as the P1, are mainly used for engine start and stop function, since engine friction losses decrease the motor power assist and regenerative braking efficiency.

- **P1:** This is an other case in which ICE and electric machine have a direct connection but this time the electric motor is positioned on the output engine crankshaft. P1 configuration is characterized by a more efficient regenerative braking function and can provide higher torque with respect to the P0.

- **P2:** The electric machine is mounted between the engine and the transmission input shaft. In this configuration a clutch is used to decouple the electric motor from the wheels, when the drive line clutch is disengaged, no engine friction losses are present, leading to a higher efficiency.

- **P3:** The electric machine is connected to the output shaft of the transmission. Most of the P3 characteristics are similar to the P2 ones but in this case regenerative braking is maximized since both friction loss from engine and transmission are eliminated when the drive line is disconnected.

- **P4:** This architecture has an electric machine connected to the rear axle drive. This architecture can enable the all-wheel-drive with the engine driving the front wheels and the electric motor driving the rear wheels. P4 together with P3 configuration have the highest energy recapture efficiency.

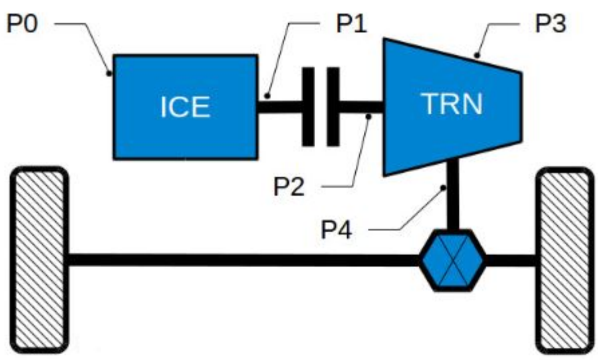


Figure 2.5: Positions of the electric motor

2.2.3 HEVs classification based on hybridization

It is possible to categorize parallel and combined hybrids according to degree of hybridization (DoH) which depends on the power supplied by the combustion engine and by the electric motor.

$$DoH = \frac{P_{\text{Motor}}}{P_{\text{Motor}} + P_{\text{Engine}}} 100\% \tag{2.1}$$

This can be seen as the percentage of power of electrical system to the total power of the power source, where P_{Motor} is the power of the electric motor and (P_{Motor}+P_{Engine}) is the total power given by the sum of the two energy sources. The definition of the DoH changes depending on the different configurations of powertrains.
According to the degrees of hybridization, HEVs can be divided into the following categories:

- **Conventional ICE vehicles**
  There is no electric motor, the engine is the only source of power and it is able to satisfy the total power requests
- **Micro hybrids (mHEV)**
  This configuration allows to shut down the engine during idle condition (Start and Stop), reducing CO2 emissions. When moving, the vehicle is propelled by the ICE. This feature is mainly used in urban areas where the speed of the vehicle is low and it may need to stop several times due to traffic or traffic lights.
- **Mild hybrids (MHEV)**
  Also in this case the Start and Stop feature is present but thanks to the presence of an EMG it is also possible to regenerate energy while braking (regenerative braking) improving the performances of the electric motor.
- **Full hybrids**
  The main characteristic of full hybrids is the possibility to work in pure electric mode, without the support of the ICE power, for small intervals of time depending on the battery capacity, (electric motor and batteries are usually bigger than that of micro or mild HEVs). In this case there is the possibility to use the engine only, the battery only or a combination of both and for this reason it requires a more sophisticated energy management system.
- **Plug-in hybrids (PHEVs)**
  It has the same configuration of a full hybrid but in this case there is the possibility for the battery to be charged through the electrical grid in order to

have a full recharge. In PHEVs, electrical component are bigger than in other implementations and the engine can be downsized.

- **Electric vehicles (EVs)**
  The vehicle is propelled by the electric motor only. The battery is recharged through the electric grid.

2.3 Summary on operating modes

Depending on the logic used to couple the two energy sources of a vehicle, hybrid cars can operate in many different ways.

- **Engine driving**
  The wheels are propelled only by the internal combustion engine.

- **Engine and motor drive (hybrid mode)**
  the energy required for propulsion is supplied simultaneously by the electric motor and the internal combustion engine. At low vehicle speed the engine is providing partial torque for the driving wheels and partial torque for the generator while the electric motor is providing drive torque using the energy from the generator.

- **Engine drive and battery charging**
  If the battery SOC is low and the engine produces more power than the one required for the motion of the vehicle, some energy coming from the engine is transferred to the electric machine which stores that energy to charge the battery. The electric motor does not output any torque.

- **Engine and motor drive and battery charging**
  Both engine and electric motor provide power to the driving wheels but part of the power from the ICE is also transferred to the generator to maintain the state of charge.

- **Energy recuperation**
  It is also called regenerative braking and it allows to recuperate energy during the braking action (energy that would be wasted otherwise). the electric motor becomes a generator which is able to convert the kinetic energy of the vehicle into electrical energy.

- **Electric motor driving**
  The engine is kept off while the battery provides all the needed power.

2.4 Energy Management System (EMS)

The main problem in hybrid vehicles consists in deciding the amount of power delivered, at each instant, by the different energy sources that are present in the vehicle architecture in order to follow a certain driving path. The control of HEVs is constituted by two main controllers: a low level controller and a high level controller. The low level controller is responsible for the energy sources on board the vehicle to provide the exact amount of requested power, while the high level controller is responsible for the power split and optimization of the energy flow while maintaining the SOC between certain limits.
The high level controller is, in other words, the energy management system (EMS). The EMS receives the quantity of power needed to follow a specific speed profile and sends to the actuator controllers the information about the amount of torque that the components should develop. The power needed by the vehicle can be provided by the ICE, the electric motor or a combination of them.
The decision on what power split combination is better to use in a specific interval of time depends on the final objective such as the minimization of the fuel consumption and emissions, that is the aim of this work.

2.5 HEV control strategies

The kind of optimal control problems seen before are usually studied using different control strategies. Hybrid powertrain control strategies can be classified in:

- **Global optimization strategies**
  The knowledge of the driving cycle needs to be known a priori and the dynamic nature of the system is considered for optimization.

- **Local optimization strategies**
  In this case the optimization problem s restricted to the instantaneous minimization of a pre-defined cost function.

- **Heuristic strategies**
  These types of control strategies are the most common ones since they are easily implementable due to low computational requirements. A set of ruels aims at keeping the internal combustion engine within its highest efficiency region.

2.5.1 Dynamic Programming

It is one of the most common global optimization strategies. DP is based on Bellman's principle of optimality and it is capable of determining the optimal solution to

the discretized problem. Bellman's principle of optimality is based on the assumption that for any point of an optimal trajectory, the other part of the trajectory is still optimal for the corresponding problem initiated at that point [9].
The idea of this optimal control solution is to avoid an excessive number of ICE activations and deactivations and it is done by formulating an instantaneous cost function which needs then to be minimized.
First thing to do in DP is the definition of a sequence of controls and so a sequence of solutions which can represent the powersplit between the combustion engine and the electric machine in a specific driving cycle. After finding a series of power splits possibilities, a cost function is associated to the selected solutions and the optimal cost-to-go (which represents the cost to reach the end of the time horizon) is calculated for each point. The final optimal solution will be given by the path with the lowest total cost.
The advantage of using this control strategy is the possibility of applying DP both to linear and non-linear systems, constrained and unconstrained systems. DP optimization has a high computational effort and it is not possible to use it to implement an online solution since it requires a priori knowledge of the overall driving cycle.

2.5.2 Equivalent Consumption Minimization Strategy

In this strategy the global optimization problem becomes a local optimization problem which is solved at each time instant.
ECMS is based on the assumption that all the electrical stored energy used must be restored using fuel from the engine so that the difference between the initial SOC and the SOC at the end of the cycle is very small and this is done assigning a cost (which depends on future vehicle behaviour) to the electrical energy. It is possible to distinguish two different cases:

- Discharge case
  The battery power is positive so the electric motor will use energy to propel the vehicle leading to the future need of being recharged.

- Charge case
  The battery power is negative, the electric motor receives mechanical energy and converts it into electrical energy stored in the battery.

In both charge and discharge cases an equivalent fuel consumption can be associated to the use of electrical energy. The total instantaneous equivalent fuel consumption can be defined as:

$$\dot{\mathbf{m}}_{\text{eq,fuel}} = \dot{\mathbf{m}}_{\text{fuel}} + \dot{\mathbf{m}}_{\text{fuel,elect}} \tag{2.2}$$

$\dot{\mathbf{m}}_{\text{fuel}}$ is the actual fuel consumed by the engine and it is given by:

$$\dot{\mathbf{m}}_{\text{fuel}} = \frac{P_{\text{eng}}(t)}{\eta_{\text{eng}} Q_{\text{lvh}}} \tag{2.3}$$

Where $\mathbf{P}_{\text{eng}}(\mathbf{t})$ is the engine power, η_{eng} is the engine efficiency and $\mathbf{Q}_{\text{lvh}}$ is the fuel lower heating value. $\dot{\mathbf{m}}_{\text{fuel,elect}}$ represents the equivalent fuel consumption of the HEV electrical power path and it is given by:

$$\dot{\mathbf{m}}_{\text{fuel,elect}} = \frac{s(t)}{Q_{\text{lvh}}} P_{\text{batt}}(t) \tag{2.4}$$

Where $P_{\text{batt}}(t)$ is the battery power consumption and $s(t)$ is the so called equivalence factor which assigns a cost to the use of electricity.
The ECMS is highly sensitive to the value of $s(t)$ which can be calibrated beforehand for the charge sustaining operation, having in this way a constant value, or it can adapt its value in real time to adjust itself to different driving conditions (Adaptive-ECMS).
The values of the equivalence factor directly affect the vehicle fuel consumption and the trend of the state of charge of the battery. To satisfy the constraints on the state of charge, and so to keep the SOC between certain limits, a penalty function is often used, leading to the following 'new equation' of the equivalent fuel consumption:

$$\dot{\mathbf{m}}_{\text{eq,fuel}} = \dot{\mathbf{m}}_{\text{fuel}} + \frac{s(t)}{Q_{\text{lvh}}} P_{\text{batt}}(t) p(SOC) \tag{2.5}$$

Where $p(SOC)$ is the multiplicative penalty function and it is given by:

$$p(SOC) = 1 - \left(\frac{SOC(t) - SOC_{\text{targ}}(t)}{\frac{1}{2}(SOC_{\text{max}} - SOC_{\text{min}})} \right)^a \tag{2.6}$$

An important decision to make when operating with the ECMS is the choice of the equivalence factor $s(t)$. The value of $s(t)$, derived from an initial guess, is set as the first thing before running the diving cycle. According to the equivalence factor value that has been chose, the operation of the powertrain is simulated to see the behaviour of the ECMS. The state variables are looped at each time instant of the drive cycle in a post-process phase and the fuel consumption and battery state of charge time series are updated. As a final step, a check is conducted on the resulting parameters, if these parameters are different from those expected, the $s(t)$ factor is updated changing its value, otherwise the operation is concluded (see Figure: 4.5 [10]).

An analytical derivation of the equivalent fuel consumption can also be done using the Pontryagin's minimum principle, whose formulation is:

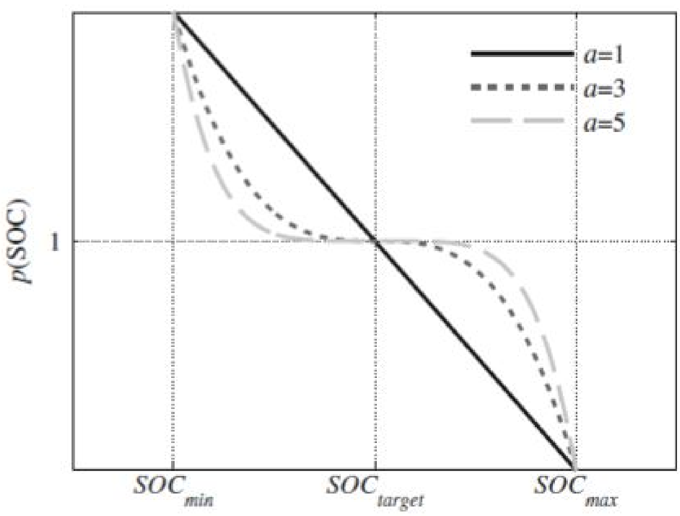


Figure 2.6: Penalty function over SOC

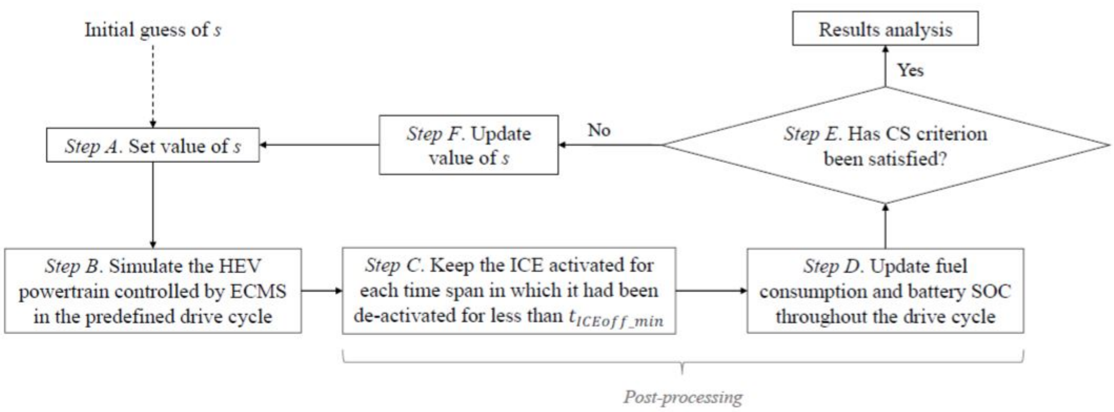


Figure 2.7: Workflow for ECMS and equivalence factor

$$H = P_{\text{fuel}}(t) + \lambda(t) P_{\text{ech}}(t) \tag{2.7}$$

where $P_{\text{ech}}(t)$ is the electrochemical power. Re-writing the formula of the total instantaneous equivalent fuel consumption (3.8) in terms of power, and multiplying each term by Q_{lvh} we will obtain:

$$P_{\mathrm{eq}}(t) = P_{\mathrm{fuel}}(t) + s(t)P_{\mathrm{batt}}(t) \tag{2.8}$$

Thus obtaining:

$$P_{\mathrm{ech}} = \begin{cases} \frac{P_{\mathrm{batt}}}{\eta_{\mathrm{batt}}} & if P_{\mathrm{batt}}(t) \geq 0 \\ \eta_{\mathrm{batt}} P_{\mathrm{batt}} & if P_{\mathrm{batt}}(t) \leq 0 \end{cases} \tag{2.9}$$

With these equations it is now possible to write the equivalence factors in charge and discharge:

$$s_{\mathrm{charge}}(t) = \lambda(t)\eta_{\mathrm{batt}} \tag{2.10}$$

$$s_{\mathrm{discharge}}(t) = \frac{\lambda(t)}{\eta_{\mathrm{batt}}} \tag{2.11}$$

The values of the equivalence factors directly affect the vehicle fuel consumption and evolution of battery charge status. Because of it, the challenge of the ECMS algorithm becomes the selection of the most appropriate values of s_{charge} and $s_{\mathrm{discharge}}$ for all the different driving conditions in order to guarantee an optimal result (Figure 2.8 [11]).

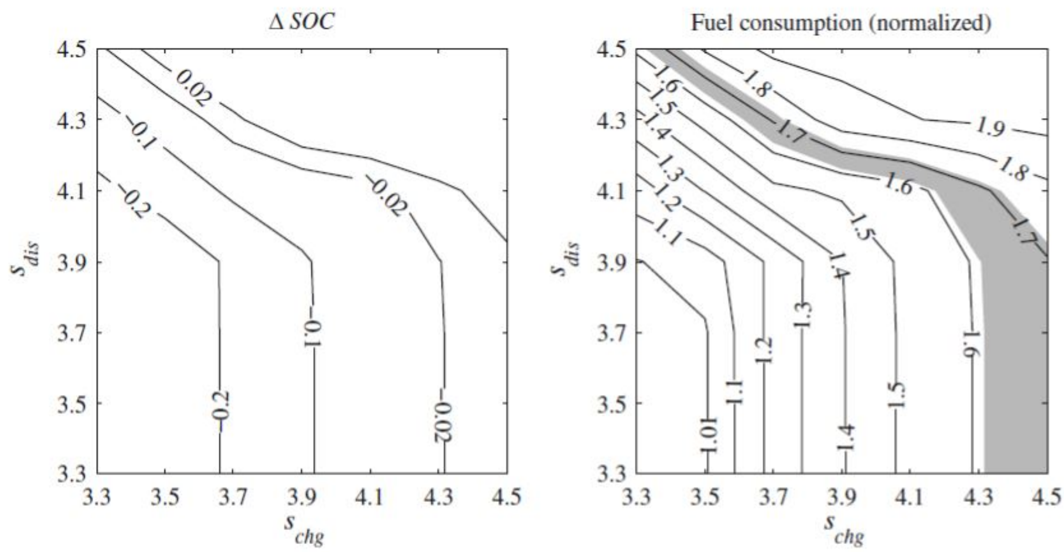


Figure 2.8: Fuel consumption and SOC variation depending on s_{charge} and $s_{\mathrm{discharge}}$ values

2.5.3 Adaptive ECMS

The optimal control methods based on instantaneous minimization such as Pontryagin's Minimum Principle and Equivalent Consumption Minimization Strategy, guarantee optimality as long as the driving cycle is perfectly known. The problem of designing a real-time implementable strategy to solve the energy management problem in hybrid electric vehicle has been studied and many solutions have been provided, one of these is the Adaptive-ECMS.
The main idea of the Adaptive-ECMS strategy was to constantly update the value of $[s_{\mathrm{ch}} s_{\mathrm{dis}}]$ (online) depending on the desired results. It is possible to identify three different adaptive techniques:

- **Adaptation based on driving cycle prediction:** The current velocity profile is related to the equivalence factor s(t) so to be able to estimate future information to feed the ECMS with the best values of s(t). Different approaches can be used to implement this techniques. In [12] the equivalence factor is estimated online based on a look-ahead horizon defined in terms of energy at the wheels and so a speed prediction technique is used while in [13] a MPC is used to establish a prediction-based real-time controller structure.

- **Adaptation based on pattern recognition:** This technique is based on the fact that the equivalence factors are similar for cycles with similar statistical properties. It is possible to see an example of adaptation based on pattern recognition In [14] and [15] where a pattern recognition algorithm is used to first identify which kind of driving conditions the vehicle is undergoing, and then to select the most appropriate equivalence factors from a predefined set. The algorithm stores these values in the memory and uses them to adapt itself depending on the driving cycle.

- **Adaptation based on feedback from SOC:** The main idea of this approach is to change dynamically the value of the co-state at the present time in order to contrast the SOC variation maintaining its value around the target value.

2.5.4 Predictive AECMS

The predictive AECMS integrates the information given by the Intelligent Transportation Systems (ITS) such as Global Positioning Systems (GPS), Geographical Information Systems (GIS), Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication and ADAS information with the above mentioned AECMS. In [16] a speed prediction block provides a short-term prediction of the drive cycle using the information acquired through the vehicular communication network. A new formulation for equivalent factor's update law is proposed, in which the controller receives the predicted speed profile and the driver's instantaneous power demand and decides how to distribute the requested power between ICE and EM based on the minimization of the total loss.

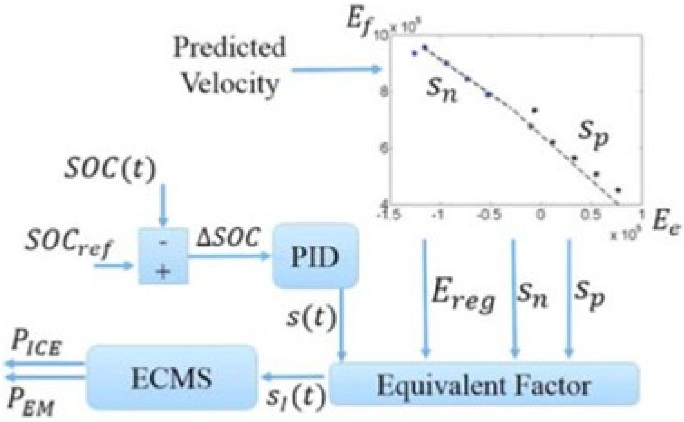


Figure 2.9: Predictive AECMS strategy

In [17] the predictive control framework distinguishes two modules: the performance and robustness modules. The Performance module consists of the predictive cycle generator, which uses real-time traffic flow data, traffic light location and a forward truck-driver model to generate distance-based predictive speed profiles. The feed-forward controller uses the predicted speed to determine the most reliable value of equivalence factor and SOC reference trajectory for each prediction horizon with the Monte Carlo approach. The robustness module applies SOC feedback control to track the SOC reference trajectory with the actual battery SOC using a correction factor. The purpose of the robustness module is preventing large deviations from the SOC reference when speed prediction is inaccurate. In [18] a SOC reference is constructed with traffic information. The predictive AECMS updates the equivalence factor with a detailed short-term prediction of the velocity profile based on the difference between the SOC at the end of the predicted short-horizon and its corresponding reference value. The desired SOC trajectory corresponding to this profile can be obtained by State Of Charge node planning. To achieve the desired terminal SOC, single shooting is applied by iteratively adjusting the initial value of the equivalence factor.

2.5.5 Rule based control strategies

These kinds of control strategies are usually based on heuristics or mathematical models in order to permit to the ICE to work at high efficiency points.

Relevant rules are defined for the powertrain control and the strategy is calibrated consequently. Performance maps are used to define the powersplit between the energy sources by observating the operating conditions of the vehicle. Rule based control strategies have a low computational demand, although, they are not always capable of reaching the optimality of a system and that is why several detailed constraints are needed to have a satisfactory result.

2.6 ADAS - Advanced Driver Assistance System

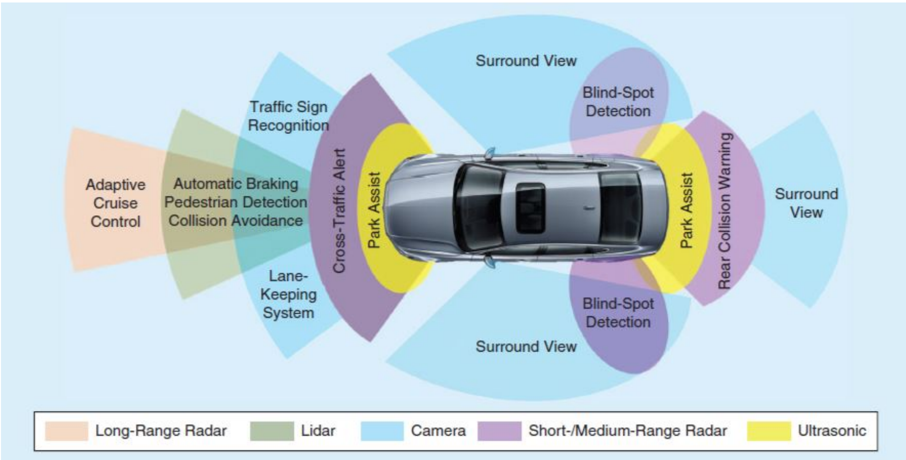


Figure 2.10: ADAS sensors

The concept of safety in automotive systems is becoming an important feature over the years and the progress in the technology field is making it possible to develop various safety systems to improve passengers conditions on the road.
It is possible to classify the safety systems into two categories:
1) Passive safety systems
2) Active safety systems

Passive safety systems are the well known 'inside-the-vehicle' applications (seat belts, air bags) which protect people from injuries in case of danger. Active safety systems are developed not only to improve instantaneous safety during a crash but also to prevent it from happening.
Different types of sensors, such as cameras, radars, lidars or ultrasonic sensors permit us to enable different ADAS solutions. Cameras are mostly used for vision-based ADAS, they are cheap with respect to the other sensors and they have an easy installation.

Radars work through microwaves, they measure the change in frequency of reflected waves and estimate the distance and the speed of an object in front of the ego vehicle. It is possible to distinguish between short range radars with an operating distance up to 30m, medium range radars (up to 80m) and long range radars (up to 200m).
Differently from radars, lidars estimate the distance from an object through the use of a radar, the distance from the object is calculated depending on the time that the light needs to go back to the sensor.
Ultrasonic sensors use the waves of the sound to measure the distance from an object and they are mostly used for short distances.
Some of the ADAS solutions which can be implemented on a vehicle are here reported:

- **ACC - Adaptive Cruise Control**
  Adaptive cruise control is a driver-assistance system which regulates the speed of the vehicle depending on the speed of the vehicles ahead in order to maintain a certain safe distance. Cameras and radars can be used for this purpose.
  Thanks to the ACC traffic flow is maximized and the driver does not have to worry about the speed. On the other hand, this is not an entirely autonomous system and so the driver needs to pay attention to the street during all the time.

- **AEB - Autonomous Emergency Braking**
  AEB is defined as a system that constantly keeps track of the road ahead, it is able to detect a potential collision and activate the braking system to start to decelerate the vehicle to avoid an imminent crush. The decision to brake is taken autonomously by the system so to take appropriate actions quickly enough.

- **Blind Spot Monitor**
  Cameras are used for the automatic parking system since they have a better view of the surrounding area. Drivers are informed when they need to stop or to steer, some systems can also complete the parking maneuver autonomously (Automatic Parking).

- **Forward Collision Warning**
  This system is able to alert the driver of a possible collision with a slower moving vehicle ahead.

- **Lane Departure Warning**
  It warns drivers when they are changing lane unexpectedly. Cameras are mainly used and when the vehicle starts to leave the marked lane, the system adverts the driver.

- **Cross-Traffic Alert**
  If any vehicle is approaching in a dangerous way, this system alerts the driver to avoid an unexpected crush.

- **Hill Descendent control**
  it takes control of the car on steep gradients by coordinating brake action through ESC and maintaining a pre-determined speed. If a vehicle accelerates more than expected, the system will automatically apply brakes to slow down the speed.

- **Hill Holder**
  It is a device that holds the brake until the clutch is at the friction point, making it easier for a stationary vehicle to start uphill. hill-holder function works by using two sensor: The first sensor measures the forward-facing incline of the vehicle, the second is a disengaging mechanism.

- **Emergency Driver Assist**
  This works by combining four driver assistance systems. If sensors detect that the driver has not used the brakes, accelerator or steering for a given time, the system initiates coordinated countermeasures. First, acustic, visual and physical warnings are sent and if he does not react, the emergency stop procedure is activated: the four emergency lights are activated, and ACC facilitates automatic braking and helps to prevent the car from hitting the vehicle in front. Even on roads with several lanes, the system steers in a controlled manner to the rightmost lane until the car comes to a stop while calling for help.

- **Traffic signs recognition**
  Using information from the front camera, it can display the speed limit depending on the road conditions.

2.7 Autonomous vehicles

Safety of the transportation users is becoming more and more important over the years and that is the reason why the automobile industry is technologically improving the features of the vehicles incorporating sensors and on-board cameras which give rise to the self driving cars. Autonomous vehicles can navigate from a source to a destination by the use of various technologies, without any human intervention, leading to a reduction in traffic congestion, fuel consumption and optimal usage of the road infrastructure. Automated vehicles are programmed to avoid accidents and cause less disruptions in road traffic understanding the situation in time and coming with a suitable counter-measure. To have a successful autonomous vehicle, an ecosystem consisting of road-side units (RSUs) and vehicle to vehicle (V2V) communication infrastructure needs to be developed, a high level of interaction between these devices can give rise to cooperative driving and increase safety and functional benefits, although, any failure of these devices, including radars, lidars and cameras, could cause serious consequences. Furthermore, as these are vehicles are operating using computing technologies, the security and privacy aspects is a very important field of study [19].

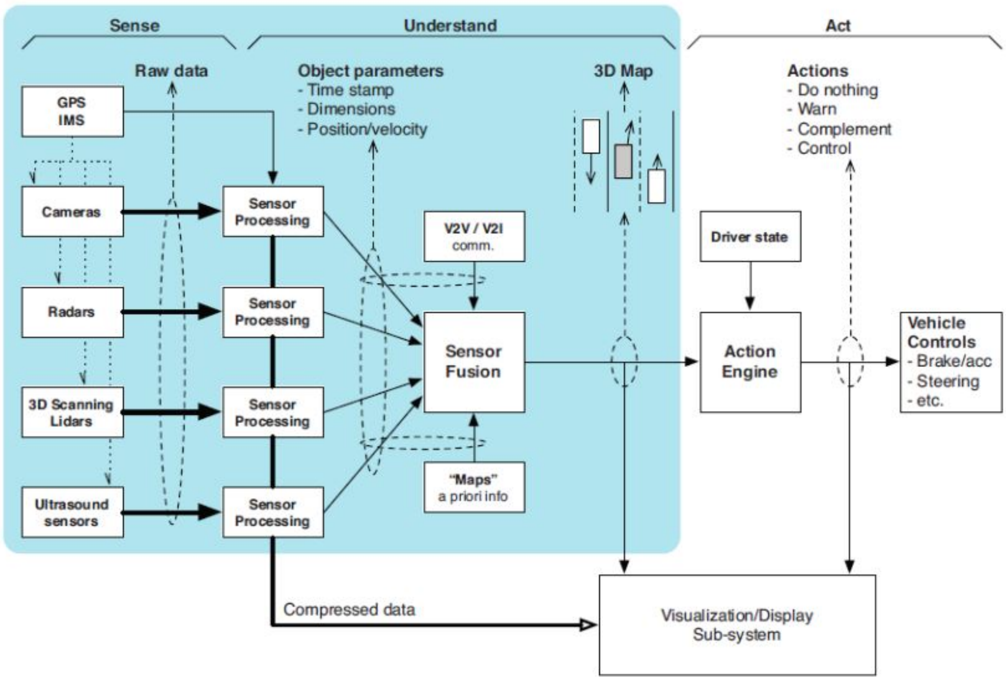


Figure 2.11: Data flow in autonomous vehicles

Even though there are many advantages to implementing these particular vehicles, their adaptability on a large scale is still in question. New companies such as Tesla or Google are challenging the traditional manufacturers, with some of them being on the market already. Testing of AVs in the US started in 1995 when an experimental autonomous vehicles developed by Carnegie Mellon University drove from Pittsburgh to San Diego. Other platforms like Uber of Lyft are also developing and testing autonomous taxis.
The Society of Automotive Engineers (SAE) defines 6 different levels of driving automation ranging from 0 (fully manual) to 5 (fully autonomous):

- **Level 0 - No Automation:** The level 0 vehicles are manually controlled without the presence of automated systems. The human performs all the driving tasks having so the responsibility of controlling the surrounding environment, although, there could be systems to help the driver which are not categorized as automation systems since they do not drive the vehicle (ex. Parking sensors)
- **Level 1 - Driver Assistance:** The vehicle has one type of automated functionality such as cruise control which maintains a constant speed along the desired route, lane keeping assistance and automatic braking. The system is always able to inform the driver in case of danger while the driver needs to be in complete control of the situation.
- **Level 2 - Partial Automation:** Here we find the presence of Advanced Driver Assistance Systems (ADAS) through which the vehicle is able to control the acceleration, deceleration and steering actions. In a level 2 vehicle the driver may have less interaction with the pedals but has full responsibility for the vehicle and can take the control at any time.
- **Level 3 - Conditional Automation:** The vehicle can perform most driving tasks and has now the capability to detect the environmental conditions and make decisions by itself. The driver must remain alert but his attention would be limited to cases of danger. The amount of user attention in level 3 automation is still an argument of discussion.
- **Level 4 - High Automation:** The vehicle is able to perform all the driving tasks under certain circumstances. The driver in this case does not need to be an 'active driver 'but he can be totally unaware of the external environment and intervene in case of a system failure or dangerous manoeuvres. This level of automation is still restricted to specific areas and because of it geofencing is required.
- **Level 5 - Full Automation:** In level 5 the vehicle performs all driving tasks under all possible conditions and human attention is no more required. The vehicle can avoid obstacles, identifying the route to follow, and choose the best speed depending on external conditions.

2.8 Vehicle-to-everything communication (V2X)

The V2X is a type of communication which occurs between a vehicle and a particular entity. In a more accurate definition of these kinds of communication, we may talk about vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-network

(V2N), vehicle-to-device (V2D) and vehicle-to-pedestrian (V2P). These types of communications are usually developed as a part of the Intelligent Transportation Systems (ITS). The study and the use of these kind of communication is related to the implementation of a real life communication model, providing a reliable view about the surrounding area avoiding crashes and traffic jams. With this approach the traffic management work blends invisibly into the wireless infrastructure avoiding wasting time with no reason.
V2V communication is mentioned in this thesis because of the possibility to use this technology for the development of a predictive energy management strategy for the minimization of fuel consumption.
Many researchers have investigated about the hypothesis of a speed prediction of a vehicle based on V2V communication. As an example, in [20] V2V communication together with GPS have been used to create a vehicle speed prediction based on real-world data. the results of the before mentioned work displays a higher fuel economy improvement for longer prediction horizons. Moreover, this method has the ability to use a higher quantity of information such as the lead vehicle's velocity prediction, which could be used to further improve the prediction accuracy.

Chapter 3

Vehicle model

3.1 Configuration and parameters

The model presented in this thesis project represents a light-duty commercial vehicle with electric hybrid propulsion of P1 topology Mild-Hybrid (IVECO Daily 35S14A8V). The characterization of the vehicle is possible thanks to numerical data provided by DAYCO and listed in table 3.1 and to efficiency maps of the engine (BSFC) and electric machine (an overview about the efficiency maps will be given in the next paragraphs).

Elements	Characteristics
Max Power	100 kW (136 Cv) / 3250 rpm
Max Torque	350 Nm / 1500 rpm
Length	6087 mm
Width	2010 mm
Wheelbase	3250 mm
Height	2660 mm
Mass	2610 kg

Table 3.1: IVECO Daily key characteristics

3.2 Modelling approach

A model is a mathematical, physical and/or graphical representation of a real element or element system which uses different formulas and methods to create a less complex description of it. Different are the model approaches and analysis methods that can be used to study the power management of a hybrid vehicle. Each of these approaches show the problem and relative solutions of a modelization from a different perspective, aiming at, in this specific case, estimate the fuel consumption of the vehicle. A possible distinction to do between the different modelling approaches is based on the "direction" of the calculation method adopted. In this perspective it is possible to distinguish between backward an forward approach.

3.2.1 Backward approach

The backward approach is based on the ability of the vehicle model to meet the demands of the drivecycle. It is a method in which the analysis is carried out considering a hypothetical temporal evolution of the vehicle's parameters and performances and proceeding from the drivecycle towards the engine responsible for propelling the vehicle. The powertrain components sizing is determined by the ability of the component to address both the speed and torque imposed on the components. Backward models rely on efficiency maps created based on torque and speed data, and usually produced during steady-state real world testing [21].

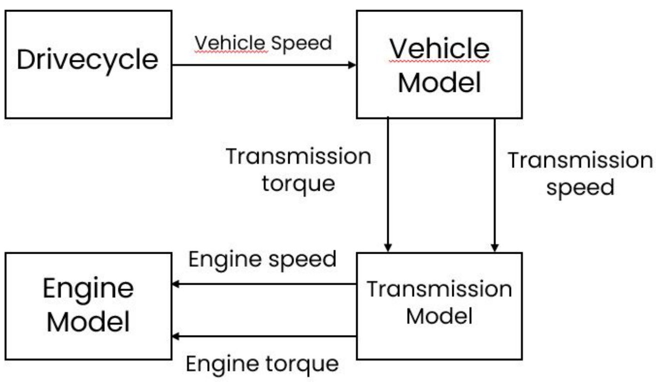


Figure 3.1: Backward approach

3.2.2 Forward approach

A forward vehicle model is a model that provides torque demand in the form of desired ICE torque in order to meet the speed trace requirements from the drive cycle. The torque produced by the ICE propagates through the transmission and ends up as the torque applied at the wheels. The vehicle speed coming from the applied force is propagated back through the drivetrain, and returns to the ICE as angular velocity at the crankshaft. In this approach the driving cycle is assumed a priori, the difference between the instantaneous speed of the vehicle and the speed given by the cycle generates an error signal which, when retroactively activated, corrects the actions of a hypotetical driver. Diffrently from the backward approach which rely on efficiency maps, the forward approach rely on multiple state equations.

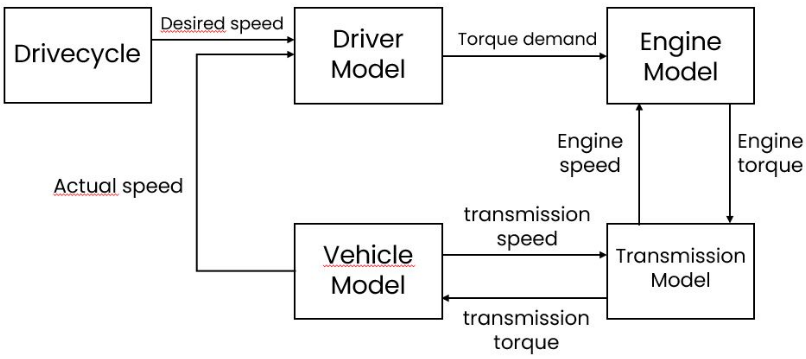


Figure 3.2: Forward approach

3.2.3 Advantages and Disadvantages of each approach

Knowing now the behaviour of both approaches, it is possible to observe the main differences between the two.

- **Backward approach:** A big advantage of backward model is the fact that it do not require a driver model, the vehicle speed trace is obtained from a given drive cycle. However, due to their quasi-static nature, backward-facing models give very limited information about the limits of the system and drivability of the vehicle [22], resulting less meaningful for implementation in hardware-in-the-loop (HIL) test systems [23].

- **Forward approach:** Forward models require the definition and the use of a model that emulates the behaviour of the driver, however, they provide a better understanding of the dynamics and physical limits of the powertrain. The forward approach deals in quantities that are measurable in a real drivetrain and with the correct causality.

These are the reasons why a forward model approach has been used for this model, where a drive cycle has been defined through standard European driving conditions.

3.3 Vehicle Model overview

The vehicle model is implemented in MATLAB/Simulink environment, MATLAB software collects input data such as vehicle parameters and efficiency maps while in the simulink interface the model (Figure 3.3) is divided in blocks, three main blocks can be identified: the ADAS inputs block, the controller and the plant, each of which will be discussed in the next paragraphs.

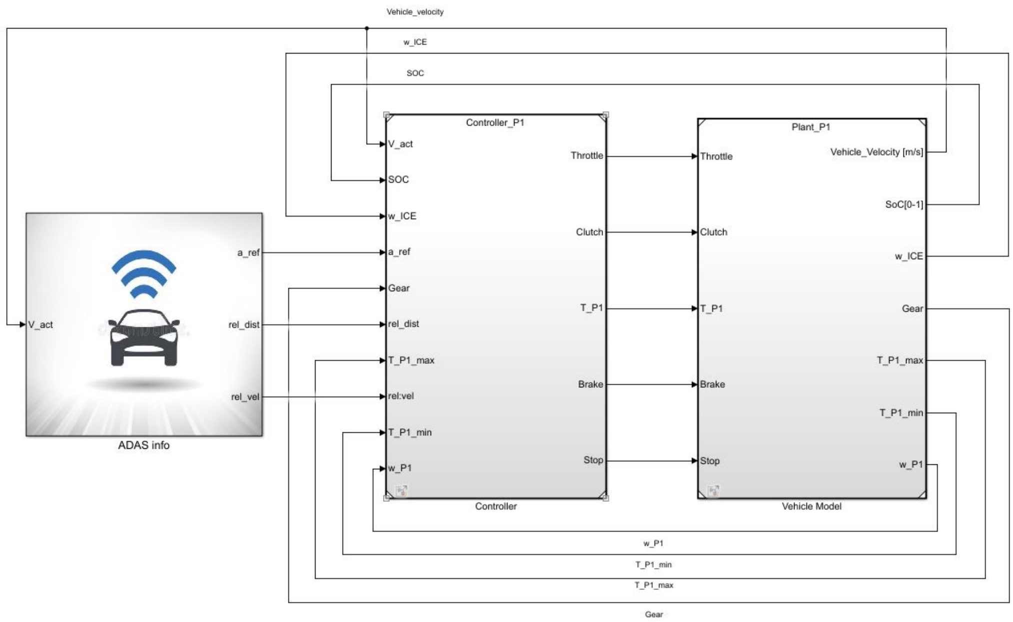


Figure 3.3: Vehicle Model overview

3.3.1 Plant

For the Plant implementation, Matlab Simscape add-on software has been used. This specific software allows you to create models of physical components based on physical links then connected with block diagrams on Simulink. The Plant block contains the model of the vehicle itself, longitudinal dynamics block is schematized through a two-axle vehicle body in longitudinal motion (from Simscape) which accounts for body mass, aerodynamic drag, road incline, and weight distribution between axles.

Longitudinal Dynamics

The primary equation of the longitudinal dynamics of a vehicle is the following [24]:

$$m_{\mathrm{v}} \frac{d}{dt} v(t) = F_{\mathrm{xf}} + F_{\mathrm{xr}} - F_{\mathrm{aero}} - R_{\mathrm{xf}} - R_{\mathrm{xr}} - mgsin(\theta) \tag{3.1}$$

where F_{xf} and F_{xr} are the longitudinal tire forces ate front and rear tires, F_{aero} is the aerodynamic drag force, R_{xf} and R_{xr} are the forces related to the rolling resistance at the front and rear tires, m is the vehicle mass, g is gravity acceleration and θ is the angle of the inclination of the road (Figure 3.4 [25]).

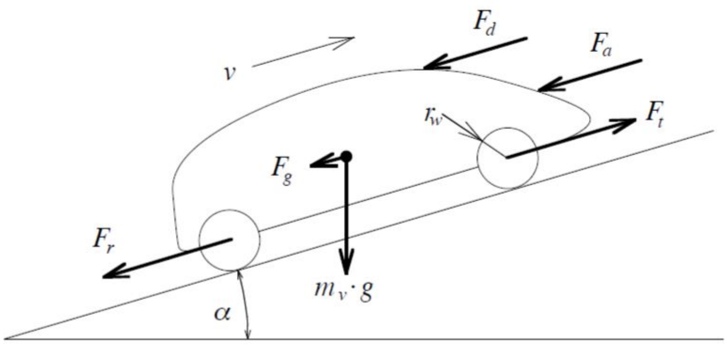


Figure 3.4: Forces acting on a vehicle

In particular, the front and rear longitudinal forces change depending on either the vehicle is accelerating or braking and they depend on the tire stiffness and the slip ratio. The aerodynamic drag force is caused by the viscous friction of the air on the vehicle surface and by pressure difference between the front and the rear of the vehicle and it is given by:

$$F_{\mathrm{aero}} = \frac{1}{2} \rho C_{\mathrm{d}} A_{\mathrm{F}} (\dot{x} + V_{\mathrm{wind}})^2 \tag{3.2}$$

where ρ is mass density of air, $A_{\mathrm{F}}$is the frontal area of the vehicle, C_{d} is the aerodynamic drag coefficient, and V_{wind} is wind velocity. The rolling resistance instead, is a resisting force that acts on the wheels caused by the interaction with the ground and it is given by:

$$R_{\mathrm{xf}} + R_{\mathrm{xr}} = f(F_{\mathrm{zf}} + F_{\mathrm{zr}}) \tag{3.3}$$

where f is a proportional constant, F_{zf} is the front normal tire force and F_{zr} is the rear normal tire force.
The vehicle speed can be calculated as a function of the forces F_{xf} and F_{xr} depending on their operating modes:

- F_{xf}, $F_{\mathrm{xr}} > 0$ (traction mode): propulsion force is sent to the vehicle;
- F_{xf}, $F_{\mathrm{xr}} < 0$ (braking mode): brakes dissipate kinetic energy of the vehicle;
- F_{xf}, $F_{\mathrm{xr}} = 0$ (coasting mode): the engine is disengaged.

Wheels

The wheels are represented in this model through a Simscape block which takes in consideration their longitudinal behaviour given the Magic Formula based on four fitting coefficients. The block is modelled as a rigid tire-wheel combination subject to slip. When torque is applied to the wheel axel, the force given by the contact friction with the ground is transferred back on the wheel pushing the wheel forward and backward. The Magic Formula is given by the following equation:

$$y(x) = Dsin[Ctan^{-}1(Bx - E(Bx - tan^{-}1(Bx)))] \tag{3.4}$$

where B is the stiffnes factor, C is the shape factor, D is the peak value, E is the curvature factor, x is the slip component and y the longitudinal force.

3.3.2 Powertrain model

The vehicle under tests is a mild-hybrid vehicle in a P1 configuration, which means that the electric motor is located on the output engine crankshaft, having so a direct connection with the ICE (Internal Combustion Engine). Mild hybrid vehicles use the engine as the primary power source and the electric motor, with a small battery pack, to produce electrical energy to assist the engine so to consume less fuel. The power-train model, shown in 3.5, consists of an engine, an electric motor, a battery and the drive-line.

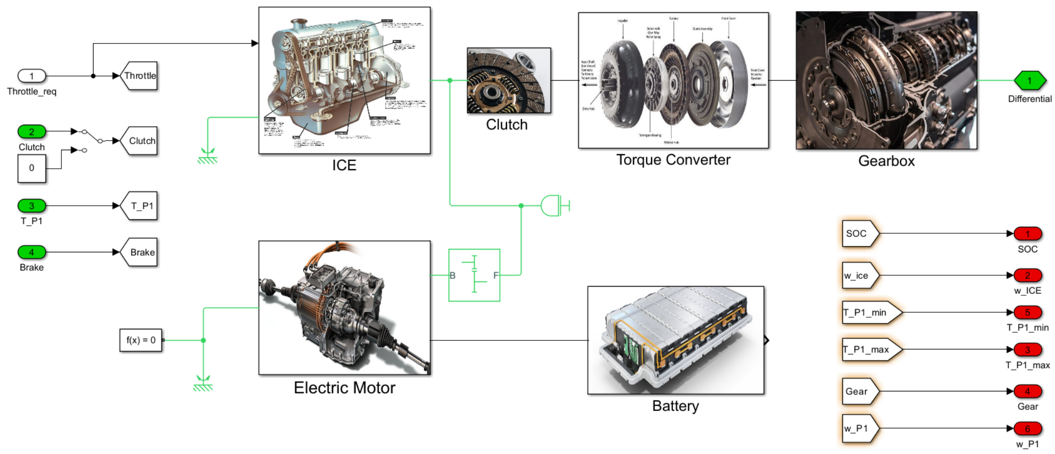


Figure 3.5: Powertrain model

Engine

The engine is a machine able to convert different forms of energy into mechanical energy. In the internal combustion engine, the combustion of fuel produces heat causing pressurisation of the gaseous combustion products in the combustion chamber which then drive a piston which turns the crankshaft.
The engine model shown in Figure 3.6 is a model characterized by a system able to impose a torque given by the high-level logic in the form of throttle and process it in terms of torque response and fuel consumed. Knowing the torque needed for propulsion, the model is then capable of evaluating the power required from the engine. A Simscape block is used to obtain the angular speed which is then sent as input to a look-up table to calculate the fuel consumption. The look-up table allows you to associate a corresponding configuration of output data to each admissible combination of incoming data by interpolation method.

The torque and the angular speed of the ICE are then used to calculate the fuel consumed by the vehicle using a fuel rate map, while the amount of CO2 emissions is correlated to the quantity of fuel injected and burned along the cycle.

Electric powertrain

The electric power-train consists of an electric machine (Figure: 3.7) and a battery (Figure: 3.8).
The electric motor defines the torque limits that can be delivered measuring the

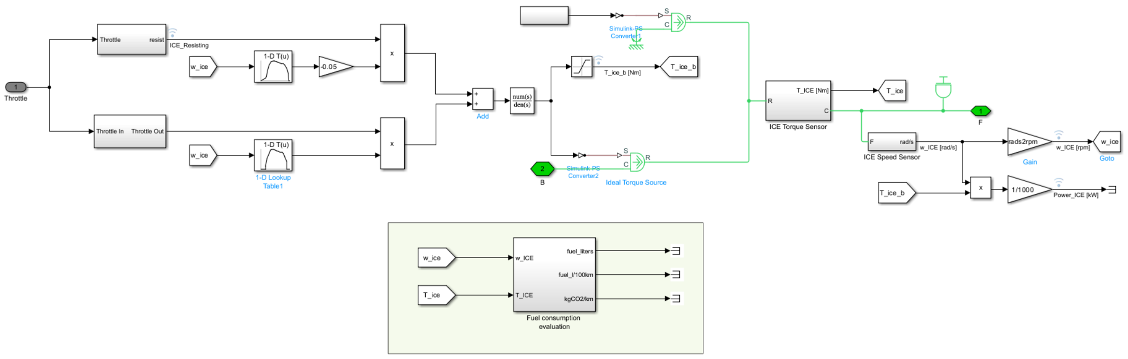


Figure 3.6: Engine model

angular velocity of the shaft and using two look-up tables, one for finding the maximum torque which can be delivered and an other one for the minimum torque. The electric machine is then able to deliver the amount of torque imposed by the control logic, converting it in power required from the battery. The machine can work either as a motor or as a generator, in motor mode when it supports the engine during the hybrid mode, delivering positive power, in generator mode during regenerative braking, delivering positive power.

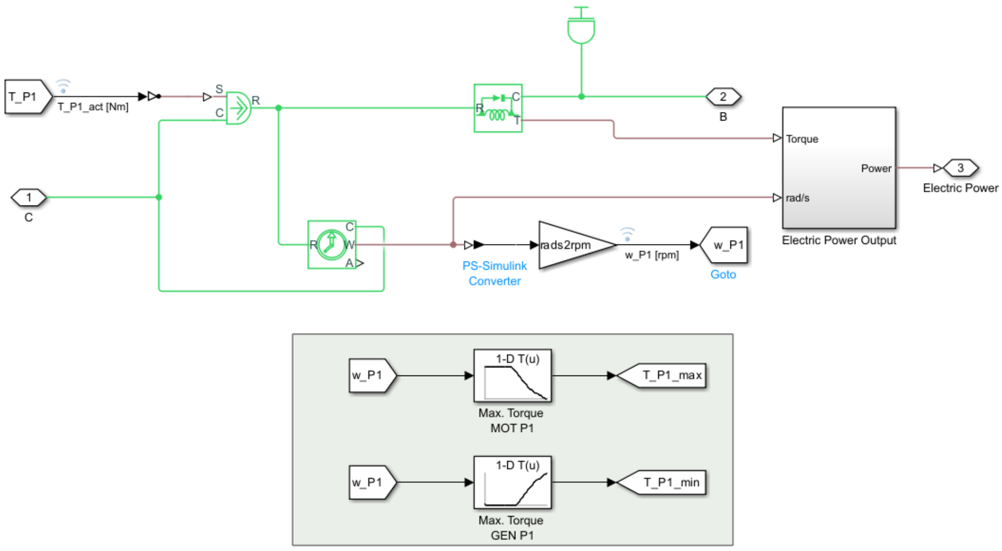


Figure 3.7: Electric motor model

To model the battery, a Simscape model has been used, inserting in the model all the battery specifications. The battery is able to both deliver and absorb energy, therefore, the electric motor can be re-charged, for example during a brake, when it is not used. Through the use of this model, it is possible to evaluate the state of charge (SOC) of the battery that is sent as feedback to the controller, which split the torque required to move the vehicle between the internal combustion engine and the electric motor. The State Of Charge is defined as the ratio of the remaining charge in the battery, divided by the maximum charge that can be delivered by the battery:

$$SOC\% = 100\frac{(Q_0 + Q)}{Q_{\max}} \tag{3.5}$$

Where Q_0 is the initial charge of the battery, Q is the quantity of electricity delivered by or supplied to, the battery and $Q_{\max}$ is the maximum charge that can be stored in the battery.

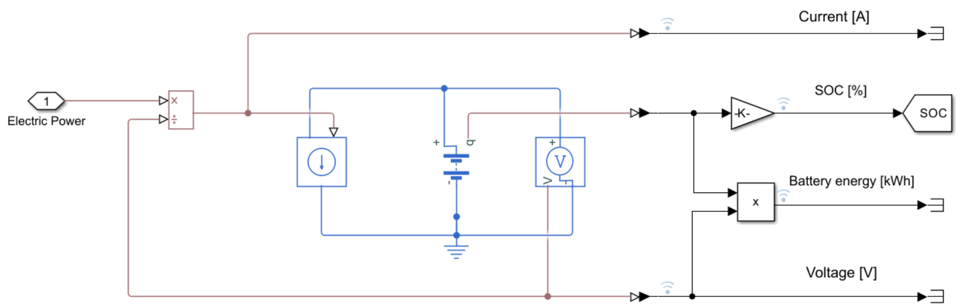


Figure 3.8: Battery model

Driveline

The drive-line represents the full force of the vehicle, including all the rotating elements and gears, it transfers power generated by the engine to the axle and, thus, to the wheels. Since the drive-line depends on the interconnection between the electric motor and the thermal engine, it is different for all the vehicle types. In particular, being the model presented a parallel hybrid vehicle in P1 configuration, the drive-line is common to both the machines.
In this specific case, the drive-line consists on a gearbox, a torque converter and a

differential. The torque converter and the differential are designed using Simscape elements and connections.

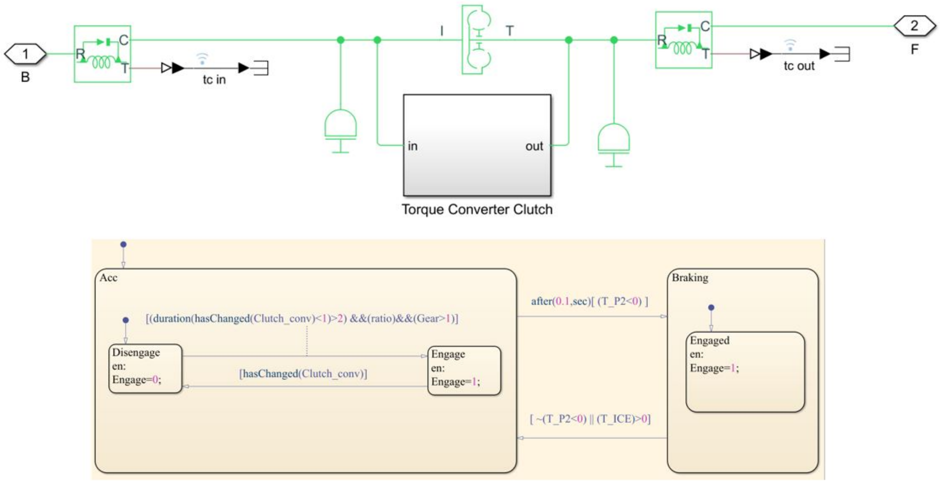


Figure 3.9: Torque converter model

The torque converter uses a fluid coupling to transfer engine power to the transmission, it interconnects the wheels and the internal combustion engine (ICE). It is an important element especially at low speed, when the load torque is mostly derived by the electric motor. The main characteristic of a torque converter is the ability to increase torque when the output rotational speed is low and to provide a reduction gear. To have enough power for acceleration and to keep the power output of the engine in the optimal range, the torque converter multiplies torque at low rpm. The engine of a vehicle must always be running, However, when the vehicle stops, the wheels, axles, and driveshaft are no longer spinning. A torque converter is then used to allows the engine and transmission to rotate independently keeping the vehicle from stalling when it is in stop condition.

The gearbox has a Simscape implementation plus a gear control logic implemented in Simulink (Figure: 3.10).

The gear ratio is computed through experimental data (Table: 3.2), then, imposing some thresholds related to the vehicle speed, the possible shifting logic has been defined.

Depending on the vehicle speed, the throttle and the electric motor torque demand, the up/down shifting logic is actuated. How we can see from figure 3.11 there is a kind of hysteresis loop into the shifting strategy. In the up shifting logic, if a certain speed is reached with a certain torque demand, the gear is changed, while

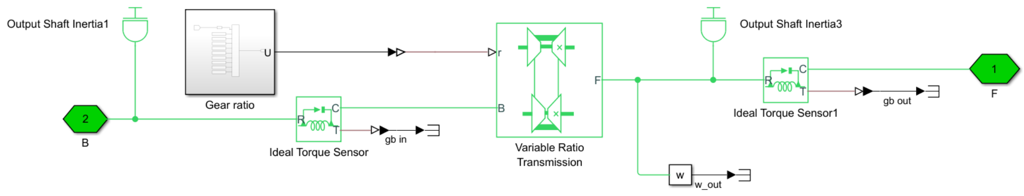


Figure 3.10: Gearbox model

in the downshifting logic, as soon as a certain lower speed is reached, the gear is downshifted.

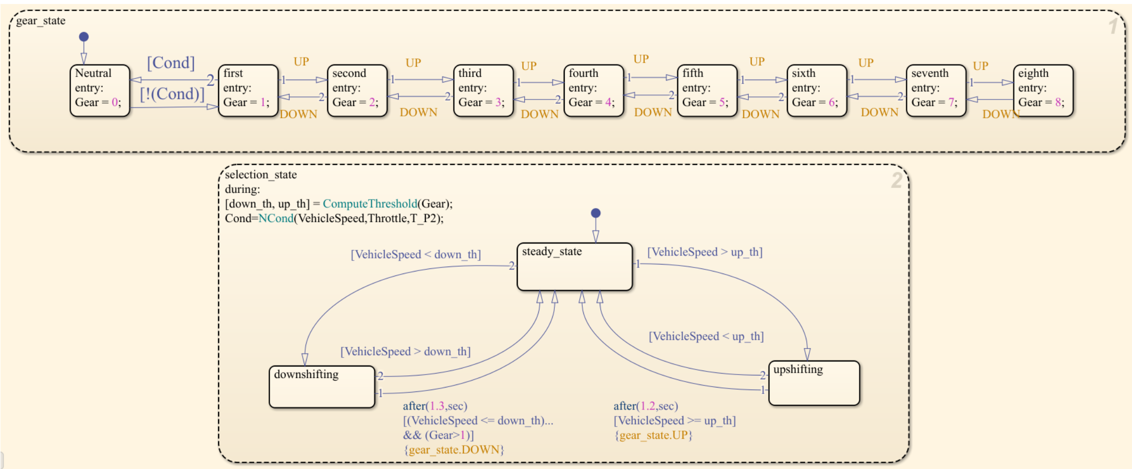


Figure 3.11: Shifting Logic

Gear	Gear ratio
1	4.714
2	3.314
3	2.106
4	1.667
5	1.285
6	1.000
7	0.839
8	0.667

Table 3.2: Transmission parameters

3.4 Efficiency maps

An efficiency map is a contour plot of the maximum efficiency of a machine in the torque-speed plane. It is used to provide insight into the performance of an electric machine when operating at various operating points, giving an idea of the overall efficiency of the drive and how well it works for maximum efficiency. It is possible to differentiate two different types of maps depending on the type of motor.

3.4.1 Brake Specific Fuel Consumption (BSFC)

The brake specific fuel consumption (BSFC) is a parameter that reflects the efficiency of a combustion engine through the use of a dynamometer (electrical brake) to measure the engine parameters (fuel mass flow rate, torque). This parameter is calculated as the ratio between the fuel requested by the engine measured as a mass flow rate in kilograms per second [kg/s] and the mechanical power [W] which is the product between engine speed and torque:

$$\mathbf{BFSC} = \frac{\dot{\mathbf{m}}_{\text{fuel}}}{w(i)T(j)} \tag{3.6}$$

Through the BSFC it is possible to determine the engine optimal operating points which are then used to develop control systems to regulate the engine as close as

possible to its optimal operation. (see Figure 3.12 [26])
Any engine will have different BSFC values at different speeds and loads, however, the efficiency often reported for a particular engine, is not its maximum efficiency but a fuel economy cycle statistical average.

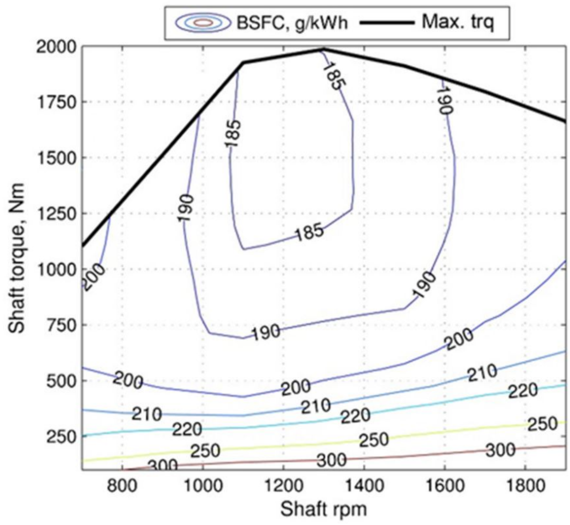


Figure 3.12: Brake-specific fuel consumption (BSFC) map of the diesel engine

3.4.2 Electric machine Efficiency Map

The efficiency map (Figure 3.13 [27]) is the plot of the maximum efficiency of an electric machine in torque-speed plane where the torque can be either positive (if the machine is working as a motor) or negative (if the machine is working as a generator). Efficiency maps and simulation are required for all electric traction motors in electric and hybrid vehicles. The machine efficiency map is obtained by finding the maximum efficiency for each torque T and speed w combination, when the combination is found, the highest efficiency of the machine is determined while satisfying the machine voltage and current limit.

The relationship between the torque (T) and the angular speed (w) and the resultant efficiency map is given by the following formula:

$$\eta = \frac{T\omega}{T\omega + T^m\omega^n} = \frac{1}{1 + T^{m-1}\omega^{n-1}} \tag{3.7}$$

which for small values of $T^{m-1}\omega^{n-1}$ becomes:

$$\eta = 1 - T^{m-1}\omega^{n-1} \tag{3.8}$$

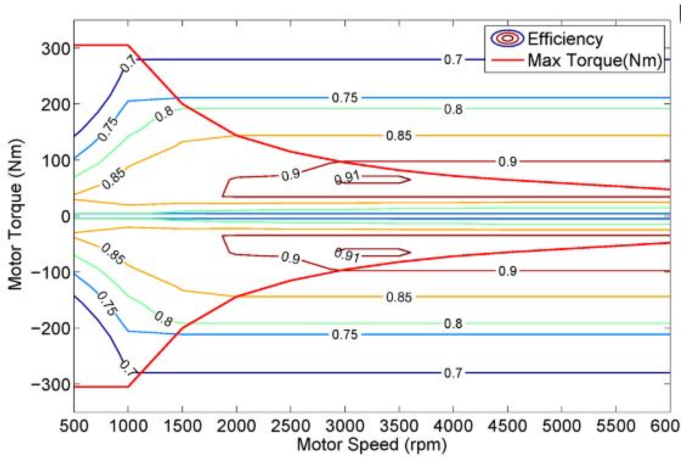


Figure 3.13: EM Efficiency map

Chapter 4

Control strategy

4.1 Controller for ICE only

The controller is responsible for performing the power management optimization of the hybrid vehicle. When working with the Internal Combustion Engine alone, the inputs that the controller receives are:

- The vehicle speed from the longitudinal dynamics block;
- The angular speed of the ICE
- The State Of Charge (SOC) from the battery;
- The gear engaged;

A drive cycle, defined in time and speed, is used to define a reference speed which, together with the actual speed of the vehicle, are given in input to a PI controller (Figure: 4.1).

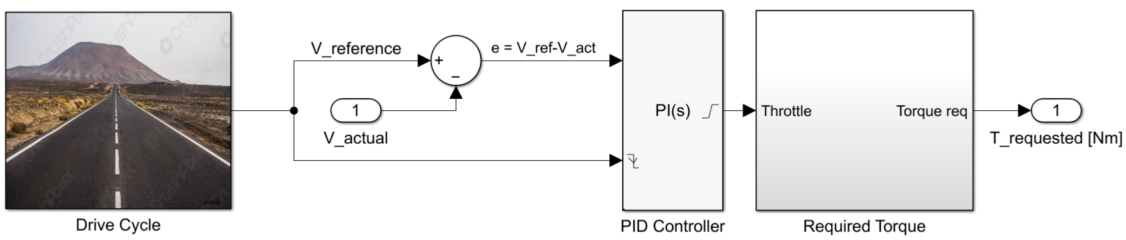


Figure 4.1: Driver model

PID control stands for proportional, integral and derivative control and it is formulated in the following way:

$$C = K_{\mathrm{p}} + \frac{K_{\mathrm{I}}}{s} + \frac{K_{\mathrm{d}} s}{s+1} \tag{4.1}$$

Where K_{p} is the proportional gain, K_{i} is the integral gain and K_{d} the derivative gain. Since in the specific case of this project the derivative control is not actuated, we will refer to it as PI controller. This controller continuously calculates an error value e(t) as the difference between a desired set-point, which in our case is the reference speed, and a measured variable (the actual vehicle speed) and applies a correction based on proportional and integral terms. Through the use of a PI controller it becomes possible to have an accurate and optimal control as output of this logic and this is why it has been used as the driver of this model. Such a controller needs to be tuned in a proper way, depending on the desired output. Since the tuning constants depend on the response characteristics of the complete model, they must be derived for each control application or in this case, for each different driving cycle.
The parameters used to tune the controller for different standard driving cycles are here reported (table 4.1). The cycles that have been mentioned here will be discussed later.

	K_{p}	K_{I}
WLTC cycle	0.35	0.3
RDE cycle	0.98	0.11

Table 4.1: PI controller parameters

The output of our PI controller is the throttle, which is given as input to a further block used to calculate the torque request, information needed for the control strategy of the system.

4.2 Controller for hybridized vehicle model

The hybridized version of the vehicle model has been developed using a specific control strategy together with the driver model described in the previous section. The inputs of the control strategy block are the following:

- The requested torque coming from the driver;

- The gear engaged;
- The maximum and minimum torque for the electric motor;
- The State Of Charge (SOC) from the battery;
- The vehicle speed from the longitudinal dynamics block;
- The angular speed of the ICE and the electric motor from the power-train of the model;

The following control strategy aims at finding the optimal power split between the electric motor and the thermal one. To do so, a Control Chart Execution has been implemented through the use of a Stateflow chart.
A Stateflow chart is a graphical representation of a finite state machine which consists of states, transitions and data. State actions define the behaviour of a stateflow chart when being active, while the transition actions are conditional actions which determines whether or not a transition to a different state occurs.

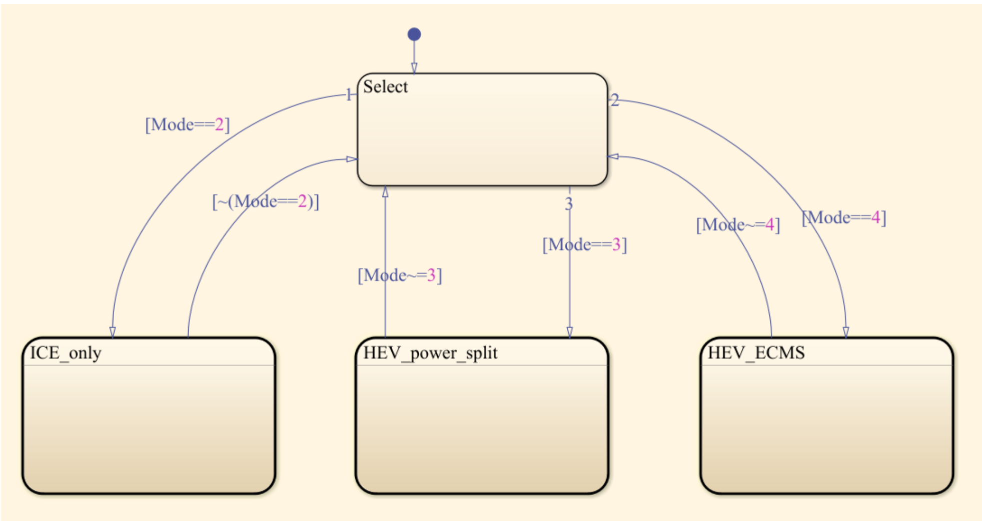


Figure 4.2: Flowchart used for the control strategy

4.2.1 Charge Sustaining and Charge Depleting

In a more standard case of a hybrid vehicle power split control strategy, a first distinction to be done is the difference between Charge Sustaining (CS) and Charge Depleting (CD) modes.

- **Charge Sustaining:** The charge sustaining mode of a hybrid vehicle maintains the SOC of the battery within some predetermined thresholds. This type of mode is implemented in the vehicles in order to prevent deep battery depletion and so to avoid future charging cost using the ICE [28]. In CS mode the battery of the vehicle is discharged by the electric motor during start and boost operation and it is re-charged during regenerative braking with the possibility so to keep the battery a certain state of charge. Charge sustaining mode is usually adopted when the drive cycle is initiated at a low state of charge in order to combine charge and discharge operating conditions. This is an interesting approach since it allows the increase of the initial charge margin preparing the motor for future events, such as low speed and torque demand, where it is more efficient to increase the discharge aggressiveness.

- **Charge Depleting:** In the charge depleting mode, the battery is discharged more than it is recharged from the generator or during regenerative braking leading to a lower SOC at the end of the drive cycle with respect to the initial target. At the end of a cycle the battery is charged through a battery charger from the grid. A long drive cycle will cause a gradually battery depletion while in the case of short cycles the discharge of the battery will be deeper so to get to the next charging point with the minimum electric energy left. This strategy, which leads to a lower fuel consumption, does not guarantee optimality since batteries depleted lose their margin of improvement against regular hybrids. Since electricity comes from the grid, generator is no more needed and batteries are usually bigger with respect to HEvs in charge sustaining mode.

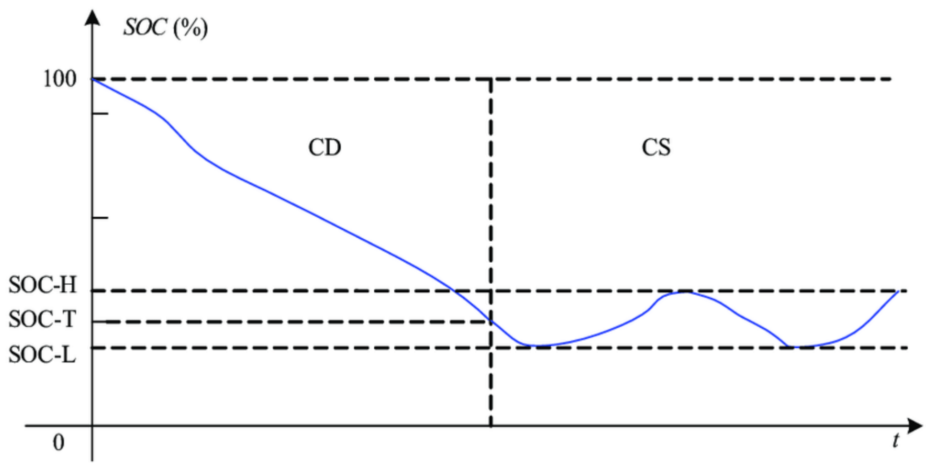


Figure 4.3: Charge Depleting (left) vs. Charge Sustaining (right)

In this specific case, of a non plug-in hybrid vehicle, the charge sustaining mode is used in order to try to keep the final SOC level at the same level of the state of charge at the beginning of a drive cycle. Knowing this additional information, it become clear that the control strategy adopted was based on the achievement of two principal targets:

- To have the same level of SOC at the beginning and at the end of a cycle;
- To minimize fuel consumption and CO2 emissions of the vehicle.

To do so, an Equivalent Consumption Minimization Strategy has been implemented.

4.2.2 ECMS algorithm

As already discussed in the Theoretical background chapter, the ECMS is an optimization strategy which takes into account the State Of Charge (SOC) of the vehicle to decide either to give more weight to the use of the electric motor or to the use of the combustion engine (ICE). This algorithm can compute the optimum solution in terms of minimization of a cost function taking as input the instantaneous conditions of the vehicle.

The basic idea of this optimization algorithm is to calculate the fuel consumption and power consumption corresponding to all possible combinations of engine and motor output torques that meet the driver's demand torque for each time instant. To do so, a cost function "J" is expressed as follow:

$$J(x,u) = \int_{t_0}^{t_\mathrm{f}} \dot{\mathbf{m}}_{\mathrm{eq,fuel}} dt = \int_{t_0}^{t_\mathrm{f}} (\dot{\mathbf{m}}_{\mathrm{fuel}}(x,u) + \dot{\mathbf{m}}_{\mathrm{fuel,elect}}(x,u))dt \tag{4.2}$$

with:

$$\begin{cases} x_{\mathrm{min}} < x < x_{\mathrm{max}} \\ u_{\mathrm{min}} < u < u_{\mathrm{max}} \end{cases}$$

where x is the state variable and u is the control variable.

So, given the state of the system, we define a range of control $[P_{\mathrm{batt,min}}(t)...P_{\mathrm{batt,max}}(t)]$ which is able to satisfy the constraints on the power, the torque and the current limits so that we can calculate the equivalent fuel consumption ($\dot{\mathbf{m}}_{\mathrm{eq,fuel}}(t)$) corresponding to each control parameter and we select the control value of $P_{\mathrm{batt}}(t)$ minimizing $\dot{\mathbf{m}}_{\mathrm{eq,fuel}}(t)$.

The control action to split the request of torque is based on two actions: braking and traction. For the braking case, the requested torque is mainly assigned to the electric motor so that it can work as a generator and recover energy. For the traction case, an algorithm calculates a vector of 100 possible split combinations.

$$\overline{u} = min\Big(\frac{T_{\text{mot,avail}}}{T_{\text{req}}},1\Big) \tag{4.3}$$

$$\underline{u} = max\Big(\frac{T_{\text{gen,avail}}}{T_{\text{req}}},-1\Big) \tag{4.4}$$

$$u = linspace[\overline{u}, \underline{u},100] \tag{4.5}$$

The vector in (4.5) is used in the algorithm to calculate all the possible combinations of requested torque. The algorithm calculates the combustion engine torque at first and then assigns the remaining torque to the electric motor. The output torque is then converted into fuel consumed and compared to the other combinations to find the optimal solution.

As stated in Chapter 2, a value of equivalence factor in charge and discharge (s_{ch}, s_{dis}) must be selected in advance, so that it is then possible to compute the engine and electric machine torque or power. The selection of the best choice of equivalence factor s(t) is the main challenge when working with the ECMS.
The control logic used for this project is an adaptive ECMS, it does not use a value of equivalence factor defined beforehand but it changes dynamically at each time instant depending on the SOC variation, keeping the state of charge between certain limits.

Different are the techniques studied and implemented in various researches to obtain the best choice of equivalence factor for each time instant. In [29] an equivalence factor MAP has been created using as parameters the SOC and the acceleratio, these parameters are real decision variables that are used to minimize the objective function. In this case the equivalence factor is fuzzy tuned using experimental experience. In [30] the EF (Equivalence Factor) is calculated through an iterative method, with the prior knowledge of the driving cycle, where the average efficiency ($\eta = \frac{\eta_{\text{m}}}{\eta_{\text{e}}}$) is used as initial EF. The initial value of EF is used to estimate a range which is then discretized at a fixed step to obtain a series of EF values. For each of these values a SOC trajectory is calculated and the EF which better satisfies the boundary conditions is chosen. A fuzzy PI controller is then used to adjust the equivalence factor for the defined ECMS in order to achieve an online adaptation law. In [31] an initial guess of the EF is done within a specific range [s_{ch}, s_{dis}], and adaptation law is then created for the equivalence factor setting a new value of it any T seconds. A V2V, V2I technology is then used to have a proper real-time strategy which takes in consideration the actual driving conditions.

In this project the equivalence factor is modelled through the use of a relay block which implements an hysteresis function based on the SOC level. The SOC level at each time instant is given in input to the relay, then, depending on the parameters used to control the relay, it outputs a multiplicative factor needed to weight the cost function.

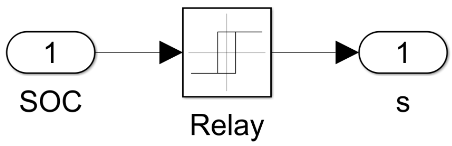


Figure 4.4: Relay used for the multiplicative factor

When the relay is on, it remains on until the input SOC goes below the value of the switch-off point (SOC level at 55%). When the relay is off, it remains off until the input goes below the value of the switch-on point (SOC level at 65%).
The multiplicative factor (s(t)), together with the above mentioned parameters, are the inputs of the ECMS algorithm function.

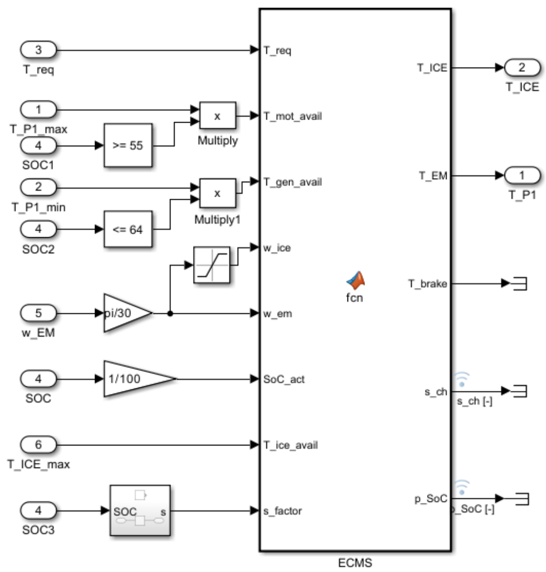


Figure 4.5: ECMS function

4.3 Controller for hybridized vehicle model and ADAS information

The energy management strategy described in section 4.2, has been further improved thanks to the use of ADAS information, which give a real prediction horizon of the driving conditions. The Advanced Driver Assistance Systems (ADAS), mostly used for safety reasons, can also be an important key in terms of minimization of fuel consumption.

In [32], for example, an optimal EMS implementation has been developed through the use of ADAS information together with a GPS location and current vehicle velocity. In this paper, a nonlinear autoregressive neural network has been used to combine all the data coming from signals and sensors in order to generate a vehicle velocity prediction. The future vehicle velocity values are predicted from the neural network from past values of the velocity and past values of each of the sensors and signals. The prediction is then used in an optimal control algorithm, dynamic programming (DP), to derive the globally Optimal EMS for that specific prediction.

An optimization approach have been proposed also in [33] where a dynamic eco-driving system consisting of an arterial velocity planning algorithm have been used for the purpose. The block diagram of the arterial velocity planning algorithm presented in [33] is shown in Fig: 4.6. The aim of the strategy consists on a quick deceleration in proximity of an intersection followed by a quick acceleration so to maintain a steady state speed while maintaining a safe distance with the other vehicle.

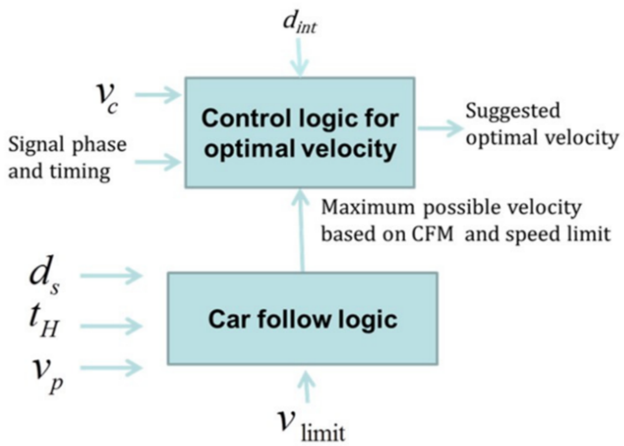


Figure 4.6: Block Diagram of the Arterial Velocity Planning Algorithm

In this thesis project an adaptive cruise control strategy have been implemented. The output of the controller is an acceleration command from which it is possible to derive the torque request needed for propulsion. This specific control logic replaces the before mentioned PI driver, transforming at first the acceleration command (with -3< a <2) into throttle (as shown in Fig: 4.7) and using this throttle, together with the gear ratio, to obtain the torque request which is then sent to the ECMS.

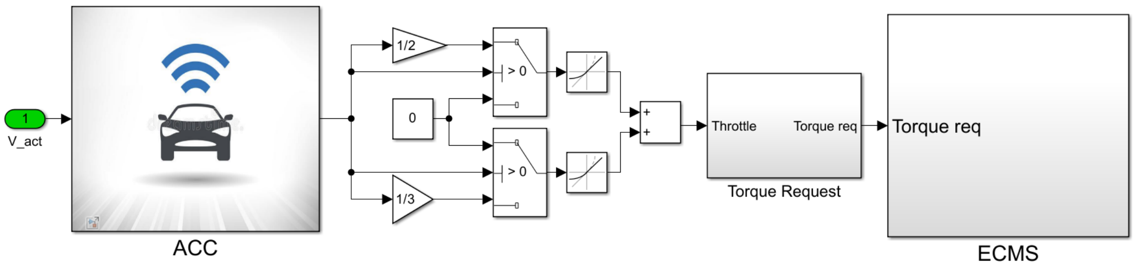


Figure 4.7: Controller for hybridized vehicle model and ADAS information

To have an optimization strategy which performs a driver's demands prediction, a space-time horizon based on European standard cycles has been developed through the use of the Driving Scenario Designer, a Matlab app which will be explained in a while.

4.3.1 European standard driving cycles

Driving cycles are speed profiles based on statistical data and implemented on chassis dynamometers to assess emissions and consumption. A vehicle must undergo a series of tests based on specific driving cycles before being approved. The cycles may be performed on a flat ground scenario, in the absence of wind. Different measurements are usually performed over a driving cycle:

- Fuel economy at different average speeds (for different driving scenarios);
- Overall fuel economy;
- CO_2 emissions.

In the framework of European homologation, the cycles used for this purpose are the NEDC (New European Driving Cycle) and the WLTP (Worldwide harmonized Light vehicles Test Procedure). A different cycle, known as RDE cycle (Real Driving Emission) is also used as a procedure to measure a car's actual emissions in real

traffic conditions. It is important to highlight that consumption and data validated in the homologation cycles are different from those obtained in actual use.
Thanks to these different driving cycles it is possible to test the vehicle with online/offline simulators.

NEDC cycle

The NEDC (New European Driving Cycle) is based on an analysis of real-world driving data derived from the German website "spritmonitor.de" [34]. This cycle starts at 0 sec and lasts for 1180 sec, emissions sampling also starts at 0 sec. It includes 4 repetitions of a Urban Driving Cycle (UDC), also known as ECE-15, followed by the EUDC (Extra Urban Driving Cycle) which is a more aggressive cycle segment. The maximum speed for the UDC cycle is 50 km/h while for the EUDC the maximum speed goes up to 120 km/h.
The set of parameters for the UDC, EUDC and NEDC cycles are reported in table 4.2 [35]

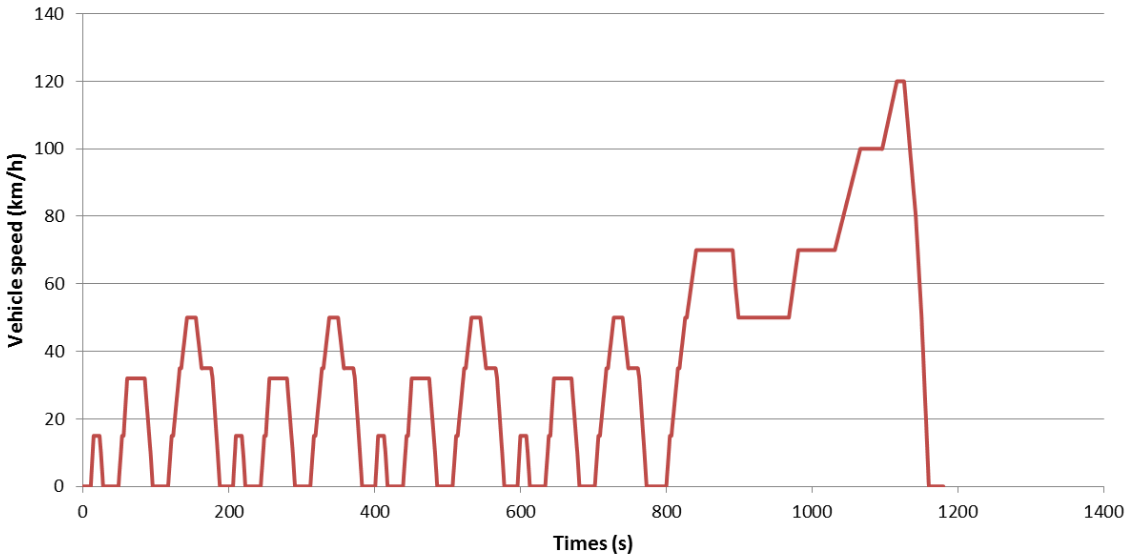


Figure 4.8: New European Driving Cycle

Characteristics	UDC	EUDC	NEDC
Distance [km]	0.9941	6.9549	10.9314
Total time [s]	195	400	1180
Average speed (excl. stops) [km/h]	18.35 (25.93)	62.59 (69.36)	33.35 (43.10)
Maximum speed [km/h]	50	120	120
Average acceleration [m/s^2]	0.599	0.354	0.506
Maximum acceleration[m/s^2]	1.042	0.833	1.042

Table 4.2: NEDC parameters

WLTC cycle

The WLTP (Worldwide harmonized Light vehicles Test Procedure) has been developed by an initiative of the United Nations Economic Commission for Europe [34]. The WLTP procedures include different WLTC test cycles applicable to vehicle categories of different power-to-mass (PMR) ratio. Class 3, With the highest power-to-mass ratio, is the most representative category of hybrid electric vehicles driven in Europe and Japan.
The WLTC starts at 0 sec and lasts for 1800 sec (the parameters of the WLTC cycle are shown in table 4.3 [35]). This cycle is divided into four phases of variable average speed, from lowest to highest, each of one, with different speed limits. The first part of the cycle simulates the urban drive with a maximum speed limit of 56,5 km/h, the second one simulated the suburban drive (medium speed) with a maximum speed limit of 76,6 km/h, the other two parts are the highways with two different speed limits, 94,4 km/h and 131,3 km/h respectively. The WLTC replaces the old NEDC in 2019 as the European homologation lab-bench procedure.

RDE cycle

The RDE (Real Driving Emission) cycle is a procedure that measures the actual emissions of a vehicle in the real traffic, with no strict driving rules as for the laboratory cycles. This cycle covers three types of driving conditions: the urban with a maximum speed limit of 60 km/h, the rural part with a velocity going from 60 km/h up to 90 km/h and the motorway for speeds above 90 km/h. Ambient conditions, stop times, and altitude are also important conditions to better specify

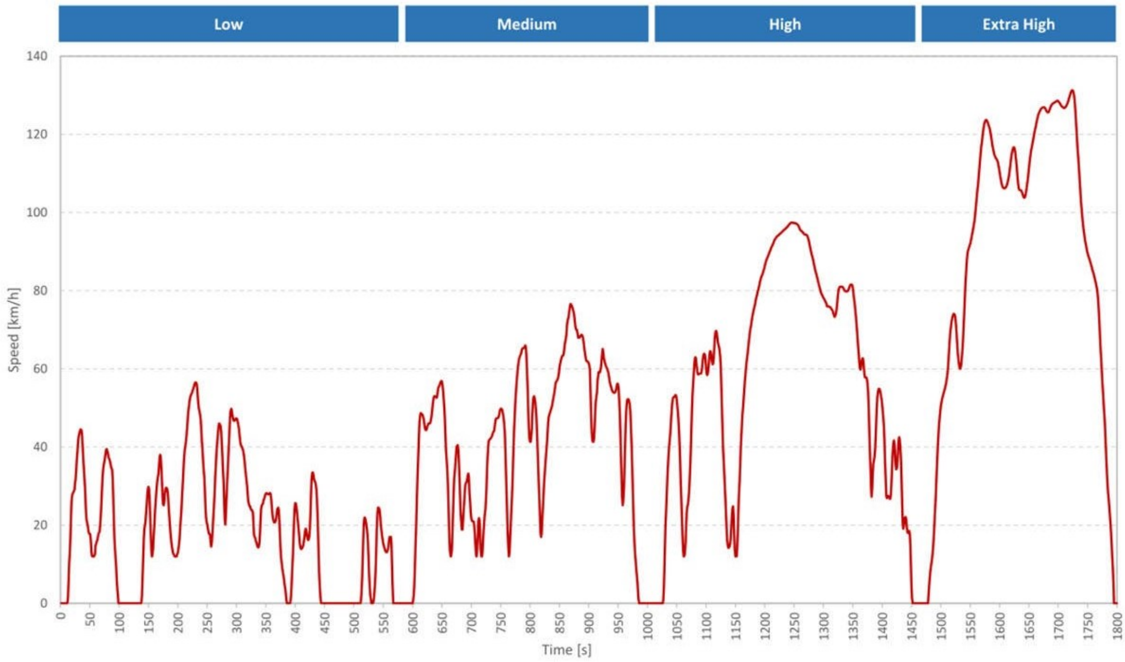


Figure 4.9: Worldwide harmonized Light vehicles Test Procedure

Characteristics	Low	Medium	High	Extra High	Total
Distance [m]	3095	4756	7162	8254	23266
Total time [s]	589	433	455	323	1800
Average speed (excl. stops) [km/h]	18.9 (25.7)	39.5 (44.5)	56.7 (60.8)	92.0 (94.0)	
Maximum speed[km/h]	56.5	76.6	97.4	131.3	
Minimum acceleration[m/s^2]	-1.47	-1.49	-1.49	-1.21	
Maximum acceleration[m/s^2]	1.47	1.57	1.58	1.03	

Table 4.3: WLTP parameters

the cycle characterization. Useful boundaries and parameters for the RED cycle are shown in table 4.4 [36].

Characteristics	Urban	Rural	Motorway
Distance [km]	>16	>16	>16
Trip composition [% of distance]	29% to 44%	23% to 43%	23% to 43%
Average speed[km/h]	15 to 40	60 to 90	>90

Table 4.4: RDE parameters

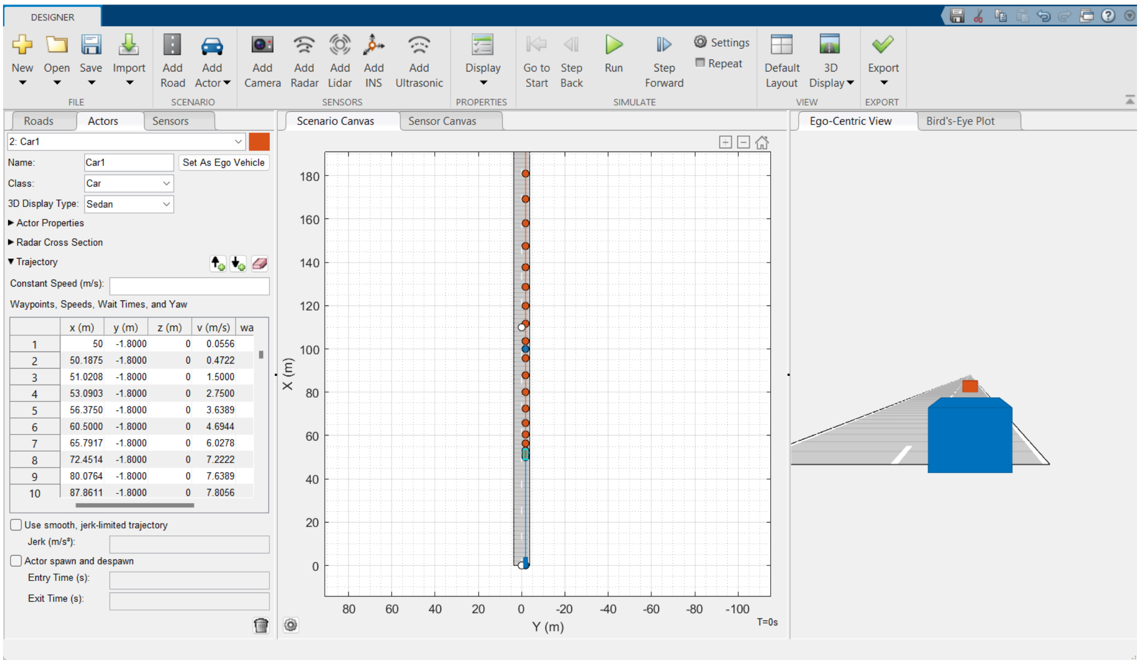
4.3.2 Driving Scenario Designer

The Driving Scenario Designer is a Matlab app which allows to design several driving scenarios for testing the autonomous driving systems. Through the use of this interface it is possible to create roads and actors models, configure cameras, radars and other type of sensors mounted on the ego-vehicle and export the final driving scenario as a Matlab function or as a Simulink model. The steps to create a driving scenario are:

- Create the road specifying the dimensions, the number of lanes for the carrigways and heading angle as a constraint to a road center point;
- Create the actors, as cars and trucks, specifying the trajectory, their pose and physical dimensions, the relative speeds at each position, wait-times and yaw angles;
- Incorporate sensors to the vehicles and configure them. In this project only a camera and a radar have been used but it is possible to add multiple sensors in different positions;
- Run the application to see the cars moving toward the desired direction and following lanes and instructions;
- Save the scenario or export it as a Matlab function or Simulink model.

The driving scenario used for this project is shown in figure 4.10. Working with only the longitudinal dynamic of the vehicle, it has been modelled a straight road in which the blue dots are the waypoints that will be followed by the ego vehicle during the test of the scenario, while the orange ones are the waypoints crossed by the lead vehicle (the one in front of our vehicle).

In this specific case, the lead vehicle is following the WLTC driving scenario described above, which has been developed through the use of the Driving Scenario Designer Toolbook, while the ego-vehicle is following the lead vehicle on the basis



	x (m)	y (m)	z (m)	v (m/s)	wa
1	50	-1.8000	0	0.0556	
2	50.1875	-1.8000	0	0.4722	
3	51.0208	-1.8000	0	1.5000	
4	53.0903	-1.8000	0	2.7500	
5	56.3750	-1.8000	0	3.6389	
6	60.5000	-1.8000	0	4.6944	
7	65.7917	-1.8000	0	6.0278	
8	72.4514	-1.8000	0	7.2222	
9	80.0764	-1.8000	0	7.6389	
10	87.8611	-1.8000	0	7.8056	

Figure 4.10: Driving Scenario Designer

of some rules defined by the adaptive cruise control strategy.
When running the scenario, it is possible to switch between the Sensor Canvas and Scenario Canvas and between the Bird's-Eye Plot and Ego-Centric view.

Bird's-Eye Scope

After running the Matlab script with all the needed parameters, it is also possible to open the Bird's-Eye Scope (Figure 4.11) on Simulink, in addition to the Simulation Data Inspector and Logic Analyzer used to log all the simulation data.

Thanks to the Bird's-Eye Scope view it becomes possible to observe how the ego-vehicle reacts to the other actors at each step time. The ego-vehicle will always be in the center of the scope of the driving scenario and road and other vehicles will move accordingly to simulate the control actions.
In order to use the Bird's-Eye Scope, you should have several blocks implemented on the Simulink model, which are needed to detect the signals from the sensors. All the blocks needed for this purpose are here listed and shown in figure 4.12:

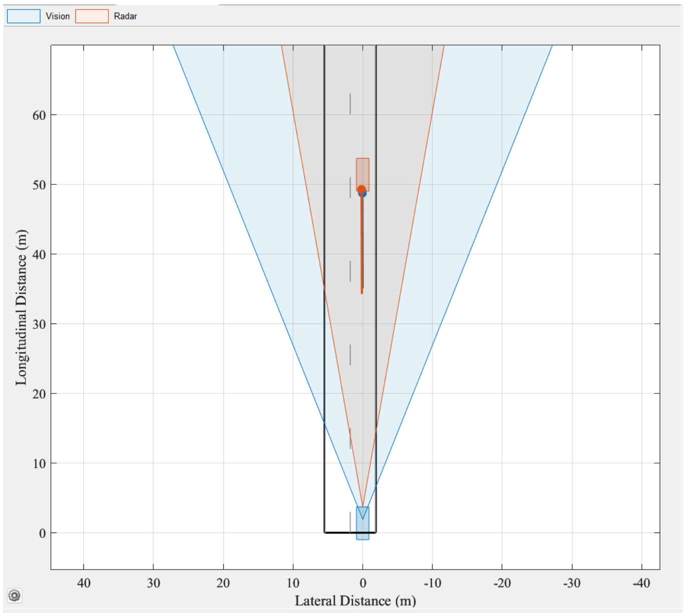


Figure 4.11: Bird's-Eye Scope

- Scenario Reader;
- Vision and Radar Detection Generators;
- Detection Concatenation block;
- Multi Object Tracker.

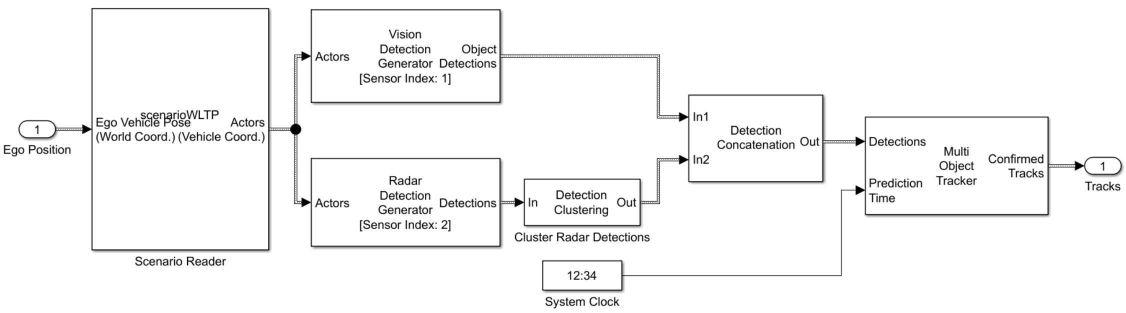


Figure 4.12: Synthetic Data Simulation

When opening for the first time the Bird's-Eye Scope, the scope canvas is blank and displays no signals, for this reason it is necessary to click on "Find signals" to update the block diagram and all the received signals, otherwise, an error will occur.

4.3.3 Adaptive Cruise Control strategy

The Adaptive Cruise Control (ACC) is an assistance system able to automatically adjust the speed of a vehicle to follow an other vehicle in front of it maintaining a safe distance. As for the classical Cruise Control, the driver can set the desired speed to follow, the vehicle will slow down when another vehicle in front of it is sensored. With ACC, adjustments on the speed profile may be more moderate than they would be without this support system, improving safety, users comfort and traffic flow because of its spatial awareness. When a system possesses multiple sensors, sensor fusion can be used to integrate different types of data and improve the efficiency and performances of the system. A camera system, for example, could notice driver's behavior such as a turn signal or brake lights, while a GPS could inform the system of geographic features.

Different researchers have focused their studies on the implementation of a control strategy based on the ACC logic to minimize fuel consumption or just to improve passengers comfort. Up to these days, most ACC designs rely on range rate measurements obtained from radar, an example of such a system is given by the Model Predictive Control.
In [37] Model Predictive Control (MPC) is used to obtain objectives of eco-driving, driving safety, comfortability and tracking capability. The MPC can adopt two different control actions: the speed control and the space control, and depending on the relative distance and velocity between the ego e the lead vehicle, the ACC system can decide the type of control action to actuate.
Also in [38] an MPC algorithm is used to minimize an objective function or the ACC system, developed by introducing the system constraints for acceleration and jerk. The work is based on a model to estimate the influence of control on the system output, by which, the future states of the system can be predicted.
In [39] the adaptive cruise control action is based on an fuzzy logic implemented to maintain the desired distance. This fuzzy logic is based on multiple constraints regarding acceleration, speed and control action limits.

The ACC model implemented in this Thesis work is based on a Mathworks example [40] which has been suitably modified, adapted to the model and incorporated into it. The ACC creates a loop in the model as it receives in input the speed of the vehicle which is then changed according to the acceleration command which is

the output of the ACC block. This acceleration, as explained before, is transformed into torque request and it is sent to the ECMS algorithm which is responsible for distributing that torque between the torque of the electric motor and the torque of the engine (Figure: 4.7).
A preview of the ACC model is shown in figure 4.13. The "Vehicle and Environment" block contains all it is needed to simulate the behaviour of the lead vehicle, from which it creates the output signals of the radar and camera. In the "Sensors" block, the signals are analyzed and the necessary information is extrapolated.

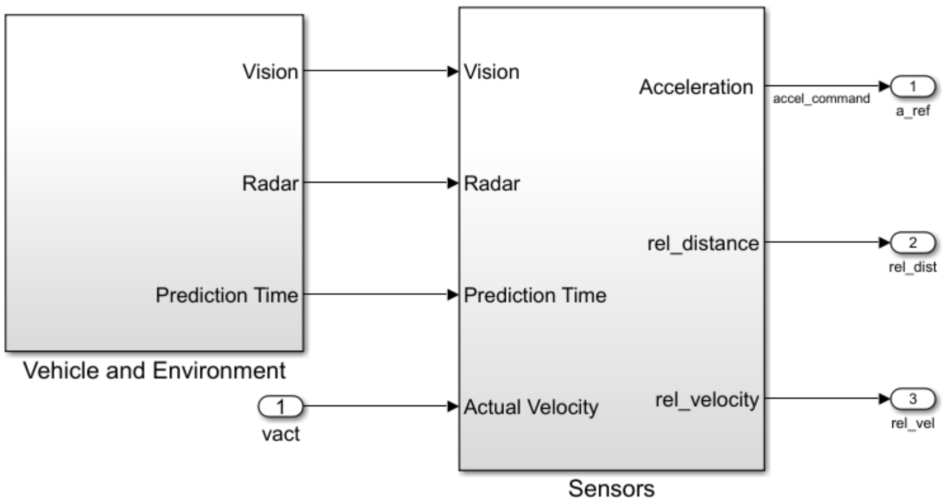


Figure 4.13: Simulated ADAS model

All this information is used to ensure the correct operation of the Adaptive Cruise Control logic shown in figure 4.14. This control logic receives in input:

- The actual velocity of the vehicle coming from the plant (v_act);
- The information about the relative distance and relative velocity between the two vehicles coming from the sensors;
- The value of the time gap and default spacing, which are defined in the Matlab script;
- The v_set value, which is the maximum speed to which the vehicle may travel when it does not see any other vehicle in front of it.

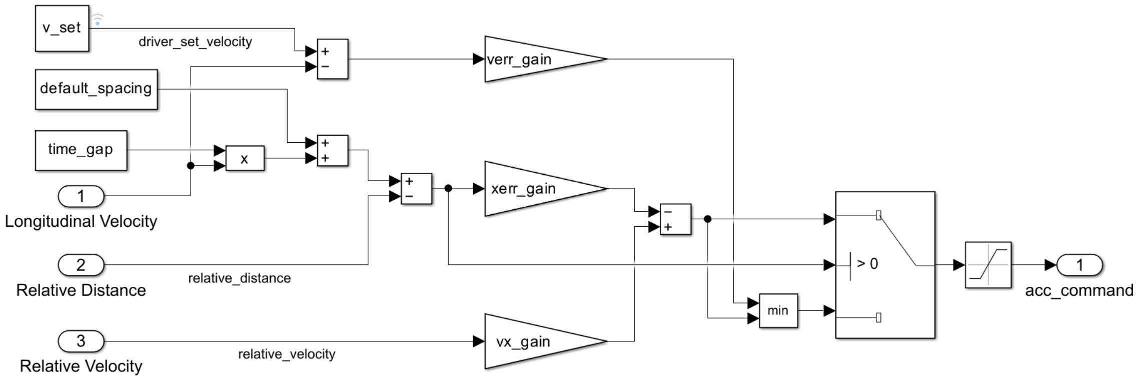


Figure 4.14: Adaptive Cruise Control logic

Since the logic heavely depends on the distance between the two vehicles over the time, sensor fusion is needed to estimate the relative velocity and relative distance to the lead car. The ACC makes the ego-vehicle travel at a specific velocity while maintaining a safe distance from the vehicle in front of it (lead vehicle). The safe distance between the lead vehicle and the ego-vehicle is defined as:

$$D_{\text{safe}} = D_{\text{default}} + T_{\text{gap}} V_{\text{act}} \tag{4.6}$$

where V_{act} is the longitudinal velocity of the vehicle and D_{default} and T_{gap} are the above mentioned parameters defined in the Matlab script.
When the relative distance is lower than the safety distance, the algorithm aims to slow down to keep the safety distance, and so obtaining:

$$a_{\text{ref}} = V_{\text{rel}} G_{\text{v\_rel}} - [(D_{\text{default}} + V_{\text{act}} T_{\text{gap}}) - D_{\text{rel}}] G_{\text{d\_rel}} \tag{4.7}$$

where V_{rel} and D_{rel} are the relative velocity and distance respectively, $G_{\text{v\_rel}}$ is the gain to weight the relative velocity parameter and $G_{\text{d\_rel}}$ is the gain used to weight the relative distance.
Replacing (4.6) in (4.9) it is possible to re-write it in the following form:

$$a_{\text{ref}} = V_{\text{rel}} G_{\text{v\_rel}} - (D_{\text{safe}} - D_{\text{rel}}) G_{\text{d\_rel}} \tag{4.8}$$

When the relative distance is higher than the safety distance, the algorithm aims to accelerate until reaching the v_set which is defined in the Matlab script, thus obtaining:

$$a_{\text{ref}} = min \begin{cases} V_{\text{rel}} G_{\text{v\_rel}} - [(D_{\text{default}} + V_{\text{act}} T_{\text{gap}}) - D_{\text{rel}}] G_{\text{d\_rel}} \\ (V_{\text{set}} - V_{\text{act}}) G_{\text{v}} \end{cases} \tag{4.9}$$

To improve fuel economy, together with the three different gains present in the formulas, two are the parameters mainly used to give weight to the control action: the default spacing and the time gap.

- The default spacing (D_{default}) is used to tune the minimum distance from the lead vehicle ensuring safety.
- The time gap (T_{gap}) is used to tune the aggressiveness on the acceleration response and for this reason it is also a factor that influences the driver's comfort.

This control algorithm, which can be compared to a constant time gap policy, has been chose because it is a Well-known approach for both industry and academia, moreover, it is implementable on real-time ECU to test effectiveness.

Chapter 5

Simulations and results

The results here displayed are the outcome of simulations over a WLTC driving scenario created with the Driving Scenario Designer Matlab Toolbox. The lead vehicle follows the WLTC driving scenario,the ego vehicle in turn, follows the lead vehicle keeping a certain safe distance from it, which is based on several parameters and is calculated from sensors. The ego vehicle follows the lead vehicle with an initial space gap of 50 meters, which is the starting position of the lead vehicle.

Section 5.1 presents an analysis of the results given from an ACC integrated with a P1 hybrid electric vehicle, where the parameters, in particular the time gap and the default spacing, are set depending on a speed dependent rule-based control logic. Since the final improvement in fuel consumption was lower than expected, a further study over specific parts of the cycle was done.
Two phases of the cycle have been studied more in deep: the urban part of the cycle and the extra urban part. To analyze the effect of the parameters $(T_{\text{gap}}, D_{\text{spacing}})$ on the speed profile, a sensitivity analysis was done with sixteen combinations of these parameters. The outcome of the sensitivity analysis displayed an opposite behaviour for the two phases of the cycle, given by the different net velocity in each case. Thanks to the knowledge given by this specific analysis, a new rule-based logic was developed, leading to a higher reduction of fuel consumption.

In section 5.2 the same control logic has been used on a non-hybridized model which uses the engine alone as source of energy.

5.1 Results based on ACC logic with ECMS

As a first strategy approach to improve the fuel economy of the vehicle, a rule-based ACC has been implemented. Some of the parameters used for the control logic implementation are fixed, while the time gap and the default spacing change depending on the vehicle speed.

After experimental tests, the value of the parameters optimising the vehicle's speed trajectory and therefore improving the fuel economy have been chosen. The value of the parameters used for this first strategy approach are listed in table 5.1 and 5.2.

Fixed parameters	
v_set [m/s]	40
$G_{\mathrm{v\_rel}}$	0.5
$G_{\mathrm{d\_rel}}$	0.2
G_{v}	0.5

Table 5.1: Fixed parameters

Speed [km/h]	Time gap [s]	Default spacing [m]
0 - 50	15	8
50 - 90	10	6
90 - 110	8	6
110 - 130	7	12

Table 5.2: Speed-varying parameters

The resulting vehicle speed profile is the one shown in figure 5.1. As it can be seen, the ego vehicle follows the lead vehicle with a small delay because of the initial space gap. The speed profile is smoothed with less restart from zero speed values.

Results of this rule-based ACC strategy in terms of fuel consumption are given in table 5.7 where it can be observed an improvement of almost 2% with respect to the model without ACC.

To further improve the fuel economy, an analysis on specific regions of interest of the WLTC cycle was done. The WLTC cycle, as explained in the previous chapter,

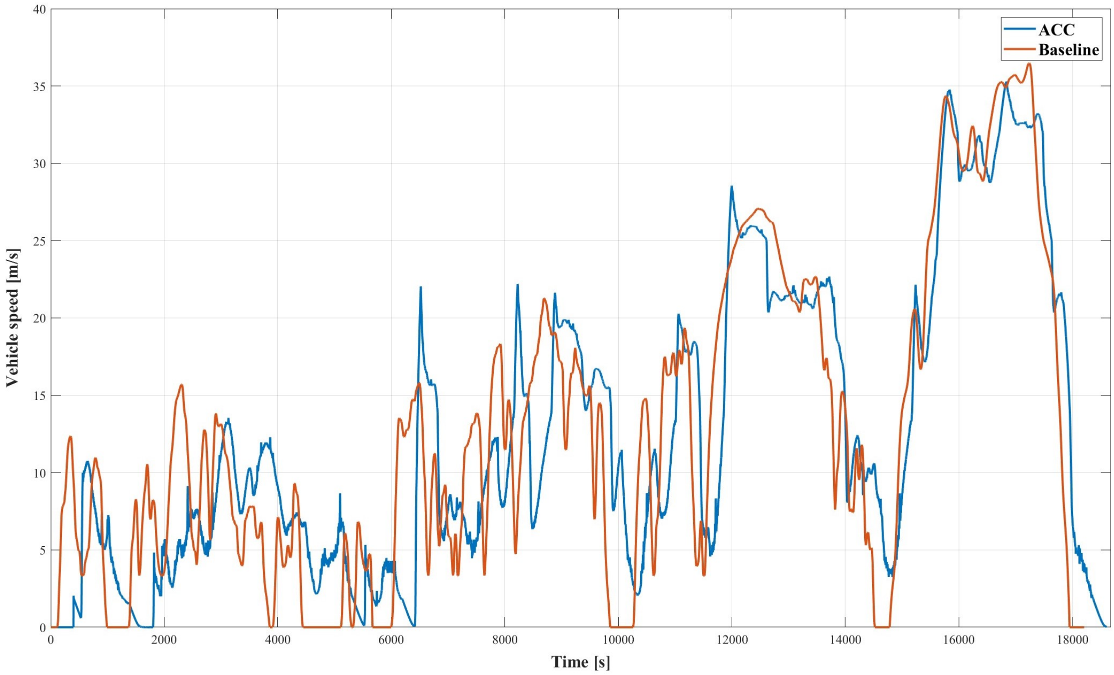


Figure 5.1: Preliminary results: Lead vehicle (orange), Ego vehicle (blue)

P1 HEV no ADAS [l/100km]	P1 HEV with ADAS [l/100km]	Improvement [%]
10.30	10.10	-1.95

Table 5.3: Preliminary results: Fuel consumption

can be divided into four different parts depending on the average speed.
The phases of the cycle with the lower and higher speed limit have been analyzed, finding the optimal parameters for each of these sections (the fixed parameters have remained unchanged).

5.1.1 Urban driving cycle

The urban driving cycle lasts for 589 seconds and it runs through 3.095 km. Different values of time gap and default spacing have been tested for this WLTC phase, sixteen simulations have been conducted to create a sensitivity analysis which collects the corresponding fuel consumption values for each iteration (see figure 5.2).

As it can be seen from the sensitivity analysis, the higher the time gap and the

	D_{def} =8	D_{def} =10	D_{def}=12	D_{def}=15
T_{gap} = 8	12.384	13.054	12.811	12.874
T_{gap} = 10	12.591	12.285	9.179	9.055
T_{gap} = 12	8.468	8.432	8.078	8.063
T_{gap} = 15	7.44	7.92	8.287	7.571
Fuel consumption baseline 8.731 [l/100km]				

Figure 5.2: Sensitivity analysis urban driving cycle [l/100km]

lower the default spacing, the lower is the fuel consumption.

The speed profiles generating the lowest and higher fuel consumption and the baseline speed profile are displayed in figure 5.3.

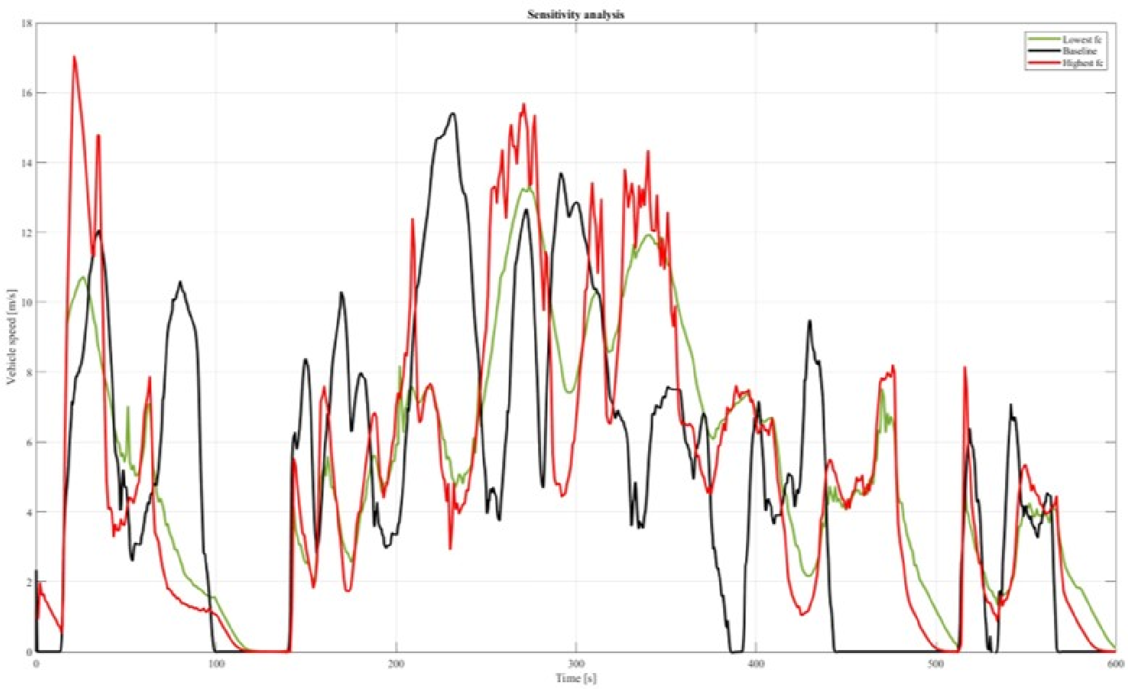


Figure 5.3: urban speed profiles: baseline (black), lowest fuel consumption (green), highest fuel consumption (red)

	D_{def} =8	D_{def} =10	D_{def}=12	D_{def}=15
T_{gap} = 8	*18.792*	*18.781*	*18.774*	*18.756*
T_{gap} = 10	*18.785*	*18.774*	*18.767*	*18.745*
T_{gap} = 12	*18.778*	*18.767*	*18.749*	*18.734*
T_{gap} = 15	*18.778*	*18.76*	*18.738*	*18.734*

Average speed baseline 17.852 [km/h]

Figure 5.4: average speeds urban driving cycle [km/h]

The average speed of each profile is almost the same (see figure 5.4) but for $D_{\text{default}} = 8$ and $T_{\text{gap}} = 15$ the speed profile (green one) is smoother with respect to the red one in which $D_{\text{default}} = 15$ and $T_{\text{gap}} = 8$. The reason why the two speed profiles are so different is the fact that in the red case (higher fuel consumption case), the distance between the two vehicles is too big, so that, sometimes, the radar and camera of the ego vehicle does not sense any other vehicle in front of it and the speed tries to reach the v_set with acceleration and deceleration peaks.

As regards the best result obtained for this specific driving cycle, the improvement in fuel economy is the following:

P1 HEV no ADAS [l/100km]	P1 HEV with ADAS [l/100km]	Improvement [%]
8.731	7.44	-14.78

Table 5.4: Urban cycle: Fuel consumption

An energy balance study was also done over the cycle. The energy balance is the analysis of energy collected by the battery or returned to it. As it can be seen from tables 5.7 and 5.6, the net energy, which is the total electric energy (spent and recovered), is lower in the ACC case compared to the case in which ADAS sensors are not taken in consideration. A lower use of the electric energy from the model with the ACC implies that the fuel consumption reduction is a consequence of an improvement in the vehicle speed profile which becomes smoother.

ENERGY BALANCE WITHOUT ACC	[kWh]
Energy required for motion	0.979
EM energy spent	0.181
EM energy regenerated	-0.264
EM Δenergy	-0.083

Table 5.5: Energy balance without ACC for the urban cycle

ENERGY BALANCE WITH ACC	[kWh]
Energy required for motion	1.384
EM energy spent	0.309
EM energy regenerated	-0.334
EM Δenergy	-0.025

Table 5.6: Energy balance with ACC for the urban cycle

In figure 5.5 it is shown the comparison between the engine power in the ACC case (in blue) and the engine power for the baseline (in orange), while in figure 5.6 the comparison is between the electric motor power of the two cases. From the pictures it becomes clear the different contribution of power given by the two sources.

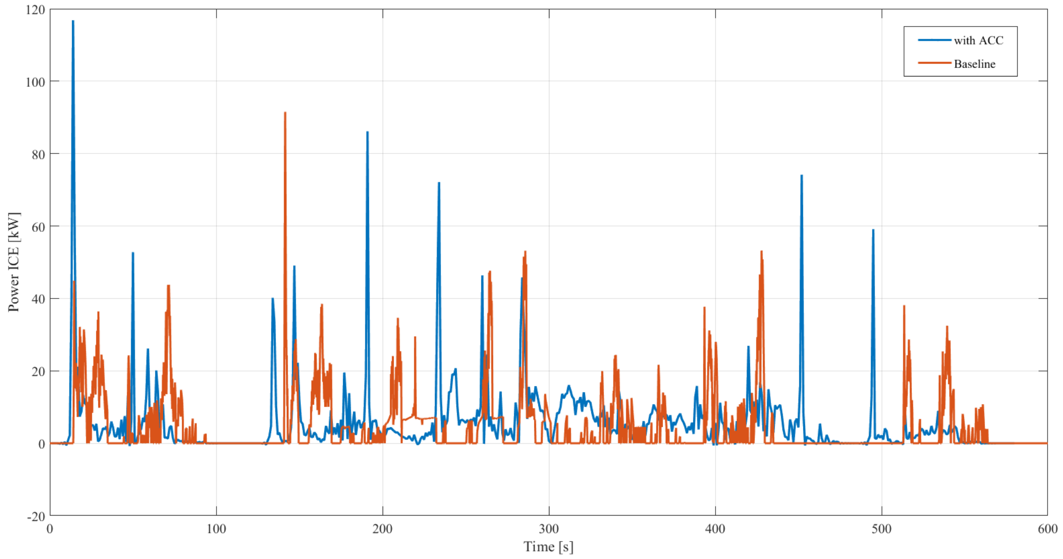


Figure 5.5: Engine power for the baseline (orange) vs. engine power for the ACC case (blue) for the urban case

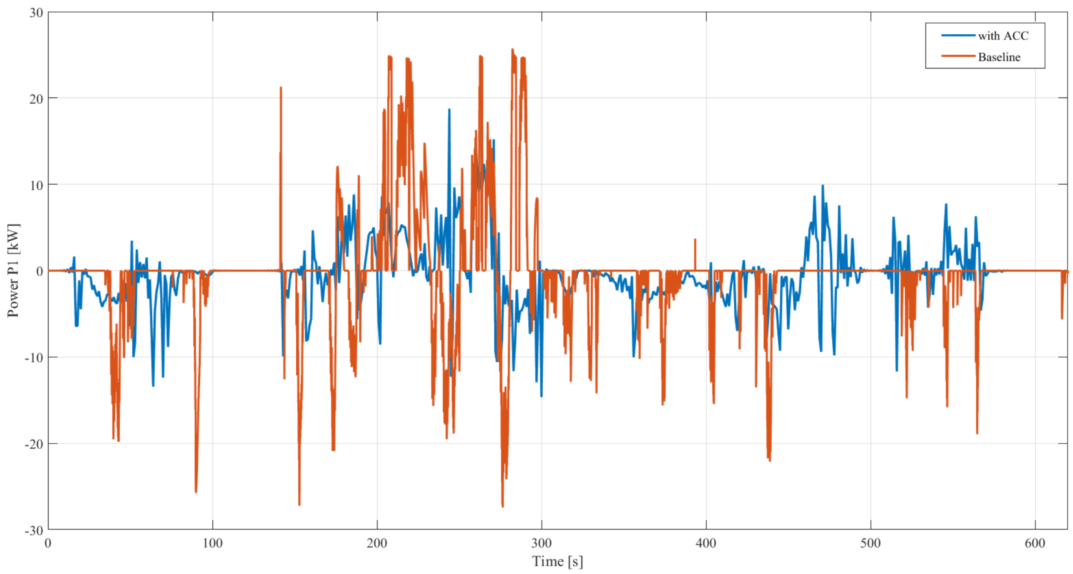


Figure 5.6: Electric power for the baseline (orange) vs. electric power for the ACC case (blue) for the urban case

5.1.2 Extra urban driving cycle

The extra urban driving cycle lasts for 378 seconds and it runs through 6.57 km. This cycle is a custom cycle created to analyse the behaviour of the vehicle in case of a higher average speed. Also in this case a sensitivity analysis has been created (5.7).

	D_{def} =6	D_{def} =8	D_{def} =10	D_{def} =12
T_{gap} = 7	9.565	9.532	9.696	9.463
T_{gap} = 8	9.663	9.7	9.668	9.77
T_{gap} = 9	10.48	10.768	10.914	10.906
T_{gap} = 10	11.757	11.539	11.794	11.858

Fuel consumption baseline 11.379 [l/100km]

Figure 5.7: Sensitivity analysis extra urban driving cycle [l/100km]

As it can be seen from the sensitivity analysis, the lower the time gap and the higher the default spacing, the lower is the fuel consumption.

The speed profiles generating the lowest and higher fuel consumption and the baseline speed profile are shown in figure 5.8. It can be noticed how different the best speed profile is (green), with smoother accelerations, compared to the worst (red) with steep acceleration and deceleration phases.

As regards the best result obtained for this specific driving cycle, the improvement in fuel economy is the following:

P1 HEV no ADAS [l/100km]	P1 HEV with ADAS [l/100km]	Improvement [%]
11.379	9.463	-16.83

Table 5.7: Extra urban cycle: Fuel consumption

Also in this case an energy balance was done (tables 5.8 and 5.9) highlighting the

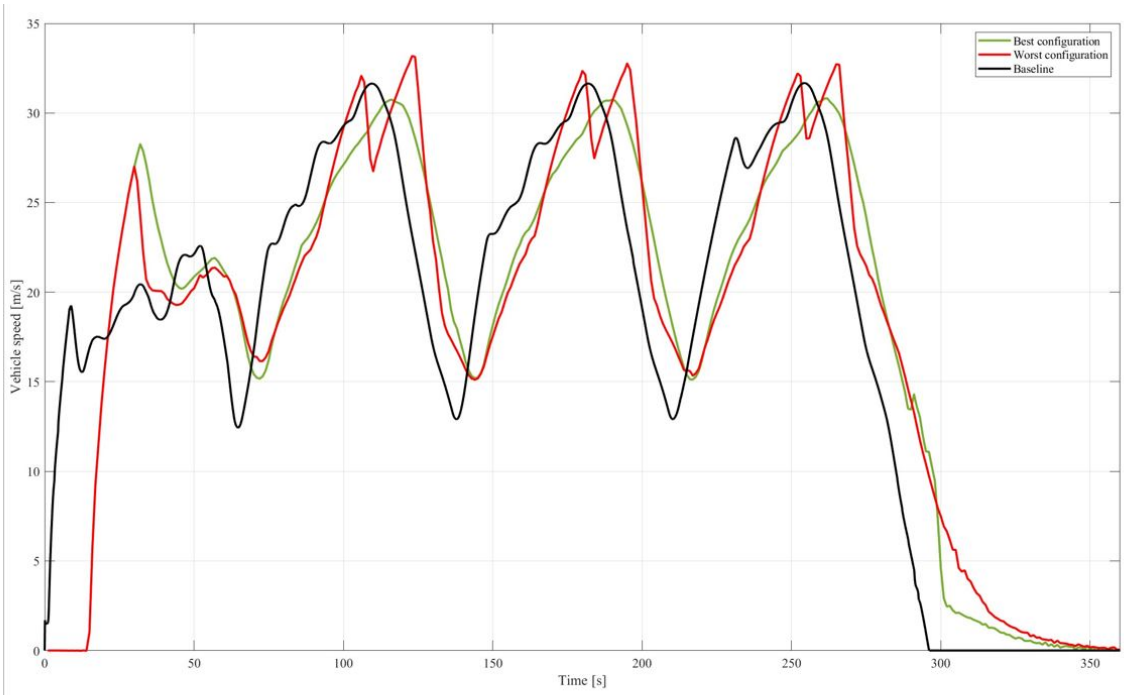


Figure 5.8: extra urban speed profiles: baseline (black), lowest fuel consumption (green), highest fuel consumption (red)

	$D_{def}=6$	$D_{def}=8$	$D_{def}=10$	$D_{def}=12$
$T_{gap}=7$	65.624	65.606	65.588	65.567
$T_{gap}=8$	65.624	65.606	65.585	65.567
$T_{gap}=9$	65.624	65.603	65.585	65.563
$T_{gap}=10$	65.621	65.603	65.581	65.56
Average speed baseline 64.645 [km/h]				

Figure 5.9: Average speeds extra urban driving cycle [km/h]

weight given to the electric motor and to the engine during propulsion. Again, the power needed for propulsion in the logic which includes ADAS information is grater but the net electric energy results lower in the ACC case. Having such a small amount of electric energy spent, even if the energy required for motion is greater with respect to the case without ACC, means that most of the energy is given by the internal combustion engine and so the improvement in fuel economy is mostly given by the speed profile.

ENERGY BALANCE WITHOUT ACC	[kWh]
Energy required for motion	3.051
EM energy spent	0.238
EM energy regenerated	-0.406
EM Δenergy	-0.168

Table 5.8: Energy balance without ACC for the extra urban cycle

ENERGY BALANCE WITH ACC	[kWh]
Energy required for motion	3.143
EM energy spent	0.245
EM energy regenerated	-0.392
EM Δenergy	-0.147

Table 5.9: Energy balance with ACC for the extra urban cycle

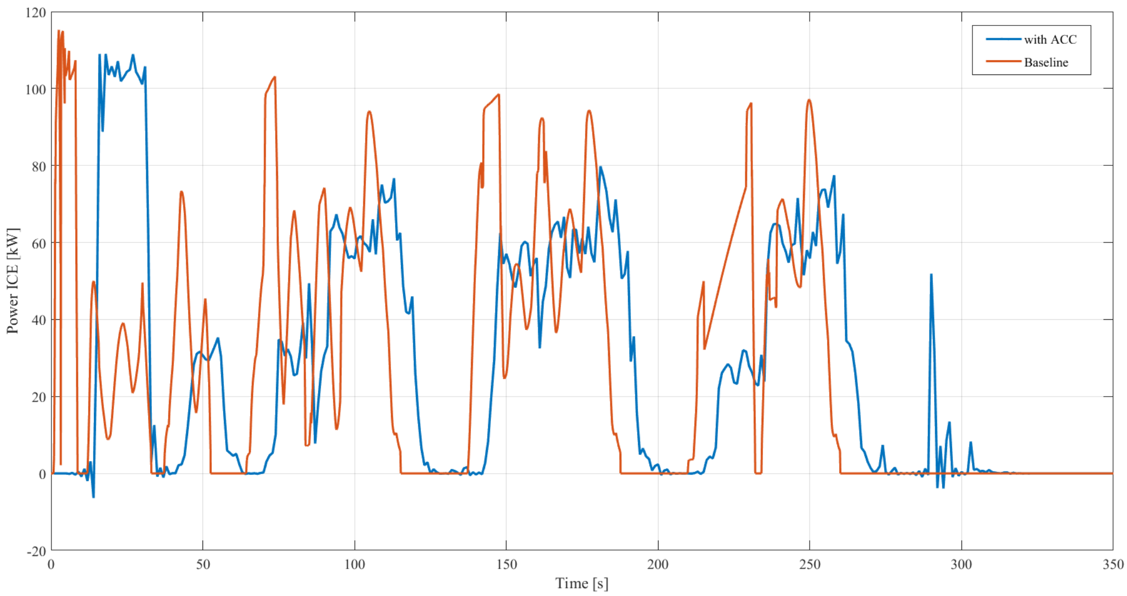


Figure 5.10: Engine power for the baseline (orange) vs. engine power for the ACC case (blue) in the extra urban case

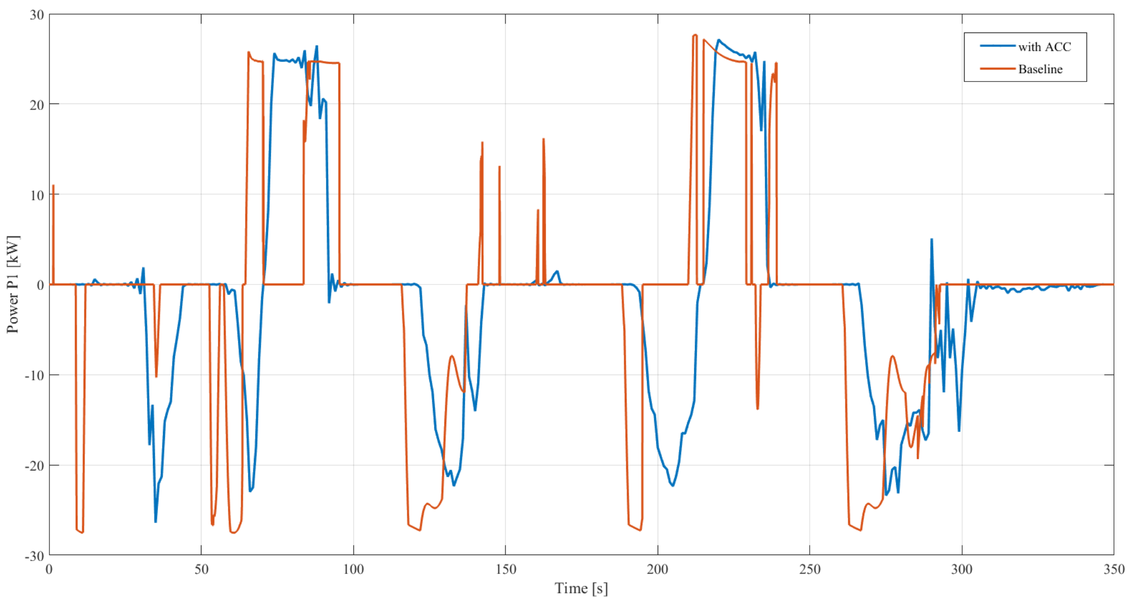


Figure 5.11: Electric power for the baseline (orange) vs. electric power for the ACC case (blue) in the extra urban case

5.1.3 Complete driving cycle

Comparing all the results obtained for the different parts of the cycle, it can be see how the fuel economy improvement for the urban and extra urban sections studied separately is much higher with respect to the one obtained by the rule-based strategy of the complete cycle.
Analysing the reasons why this happens, we understood that the control strategy based on the velocity was not effective because of the continuous variation of the vehicle speed.
Considering, for example, the extra urban driving cycle, and looking at the vehicle speed profile, it can be seen how the speed ranges from zero to 120 km/h crossing all the different speed limits defined for the logic. Every time the speed goes beyond 50, 90, or 110 km/h, the values of the time gap and default spacing change, changing so the behaviour of the ego vehicle towards the lead vehicle.

For this reason, a new rule-based control strategy was adopted.
This new strategy is not based on the vehicle speed anymore but is based on time. Through the use of sensors or inter-vehicle communication, knowing the distance to travel and the speed limits it is possible to estimate the time needed to travel a stretch of road. For the WLTC cycle, the time needed to travel each section is already given by the definition of the cycle itself.

From the previous study of the different sections of the cycle it is now possible to understand how the values of time gap and default spacing acts on the fuel consumption depending on the speed. When the average speed is lower (urban case) a better result is given in the use of a higher time gap and a lower default spacing, the opposite thing happens in the case of a higher average speed, where the fuel consumption is minimized using a lower time gap together with a higher default spacing. Using the same logic, the values of T_{gap} and D_{default} have been adapted depending on the length of time since the starting point, dividing, in this way, the cycle into four phases with different average speeds. The time gap value decreases when the average speed increases and the default spacing increases when the average speed decreases (the new values are shown in table 5.10).

The vehicle speed profile becomes even smoother with respect to the previous rule-based logic, with the absence of peaks especially in the middle part of the cycle.

The fuel economy is much higher, in percentage, with respect to the one obtained with the first strategy attempt, we get a 9.12% of improvement compared to the 1.95% of the previous try (see table 5.11).

Time [s]	Time gap [s]	Default spacing [m]
0 - 589	16	2.5
589 - 1120	12	5
1120 - 1420	9	8
1420 - 1820	7	14

Table 5.10: Time-varying parameters

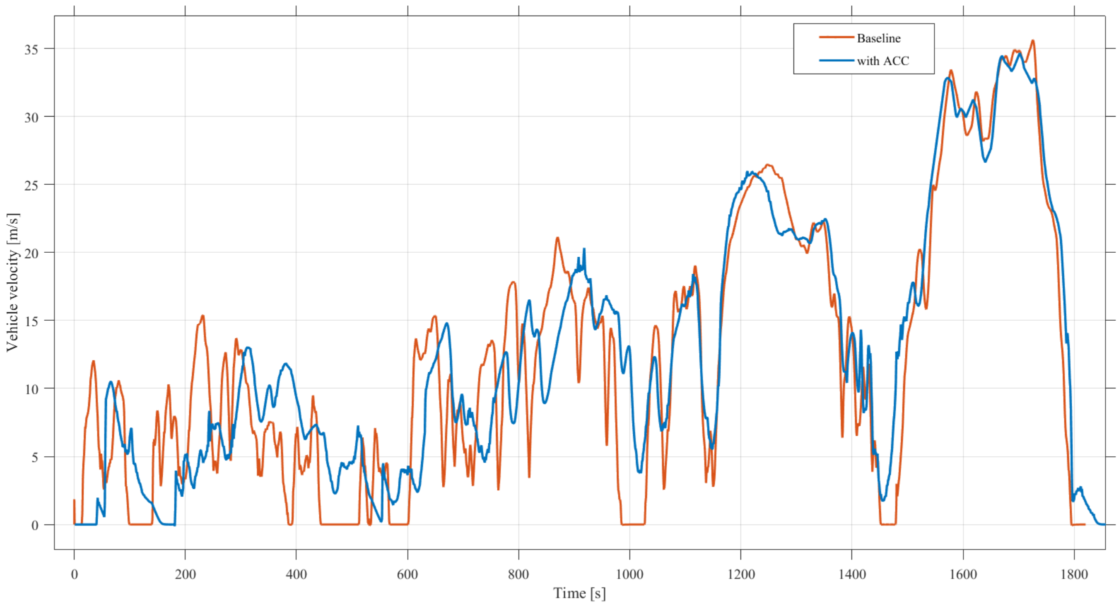


Figure 5.12: Rule based strategy: Lead vehicle (orange), Ego vehicle (blue)

P1 HEV no ADAS [l/100km]	P1 HEV with ADAS [l/100km]	Improvement [%]
10.30	9.36	-9.12

Table 5.11: Complete cycle: Fuel consumption

From the energy balance of the complete cycle it is possible to notice that the final net energy in the ACC case is higher than in the case with no ACC. The model with the ACC requires more energy for motion, but the percentage of additional energy used by the ACC (6.57%) is much smaller compared to the electric motor use percentage (35.3% with respect to the model without ACC). Even if the amount of EM energy spent is higher, and so it is for the recovered energy, at the end of the cycle, the state of charge of the battery is comparable with the initial one (60%) as it can be seen in figure 5.13.

ENERGY BALANCE WITHOUT ACC	[kWh]
Energy required for motion	8.630
EM energy spent	0.536
EM energy regenerated	-0.638
EM Δenergy	-0.102

Table 5.12: Energy balance without ACC for the complete cycle

ENERGY BALANCE WITH ACC	[kWh]
Energy required for motion	9.237
EM energy spent	0.831
EM energy regenerated	-1.121
EM Δenergy	-0.290

Table 5.13: Energy balance with ACC for the extra urban cycle

Figures 5.14 5.15 show the plots of the power used by the two different sources compared to the ones used in the absence of an ACC logic.

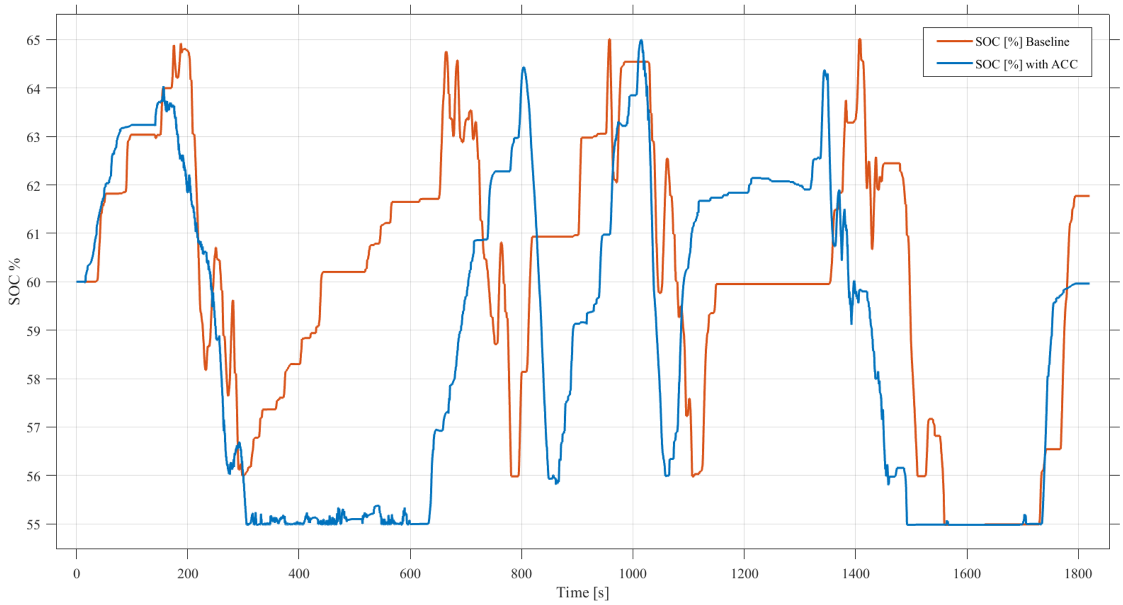


Figure 5.13: State of Charge of the battery

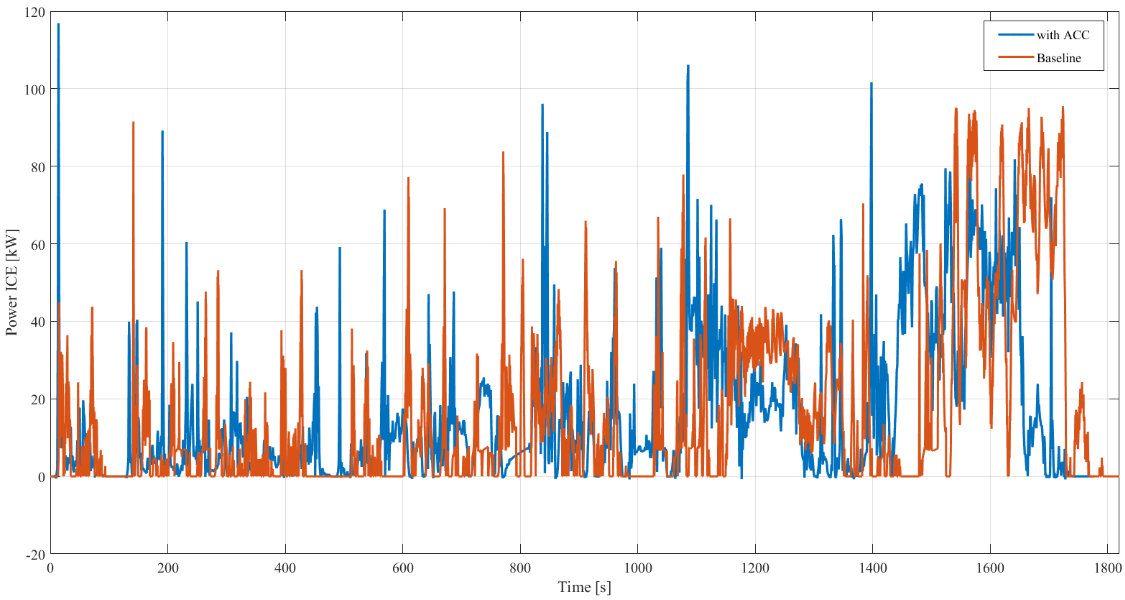


Figure 5.14: Engine power for the baseline (orange) vs. engine power for the ACC case (blue) for the complete cycle

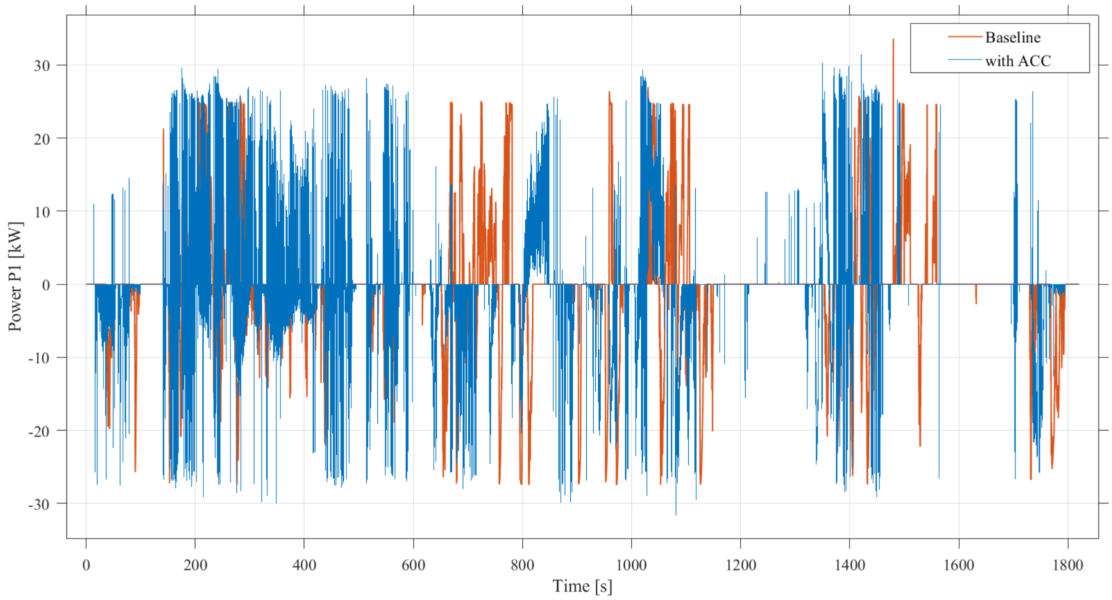


Figure 5.15: Electric power for the baseline (orange) vs. electric power for the ACC case (blue) for the complete cycle

5.2 Results based on ACC logic with ICE only

An analysis of the complete cycle was also done with the non-hybridized version of the vehicle model (ICE only mode) to see how the ACC behaves in the absence of the P1 electric motor and so without the ECMS algorithm.
The same parameters were used to run the simulation (table 5.14), obtaining the speed profile shown in figure 5.16.

Time [s]	Time gap [s]	Default spacing [m]
0 - 589	16	2.5
589 - 1120	12	5
1120 - 1420	9	8
1420 - 1820	7	14

Table 5.14: Time-varying parameters

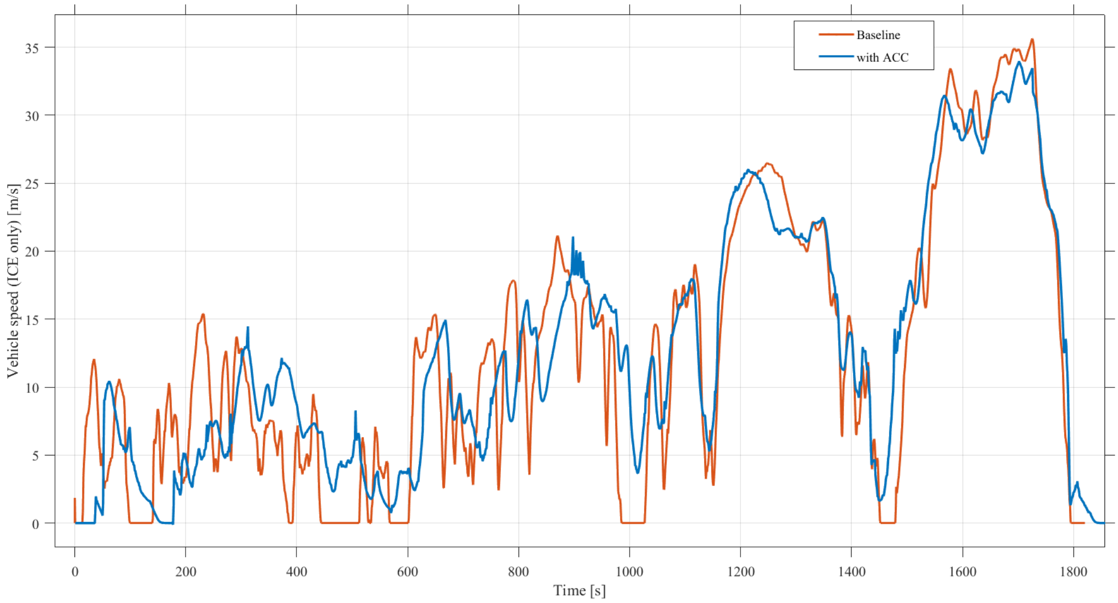


Figure 5.16: Rule base strategy for ICE only: Lead vehicle (orange), Ego vehicle (blue)

As stated before, the main contribution for the minimization of the fuel consumption is given by the smoother speed profile.Knowing in advance if an acceleration phase will occur, the vehicle does not stop unless necessary.
Acceleration and deceleration peaks are avoided and because of it, also in this case, it is possible to see a high improvement percentage in fuel economy (see table 5.15).

ICE only no ADAS [l/100km]	ICE only with ADAS [l/100km]	Improvement [%]
10.981	9.807	-10.69

Table 5.15: Complete cycle (ICE only): Fuel consumption

In this case there isn't any power requested or coming to/from the electric motor, the only power contribution is the one coming from the internal combustion engine (figure 5.17).

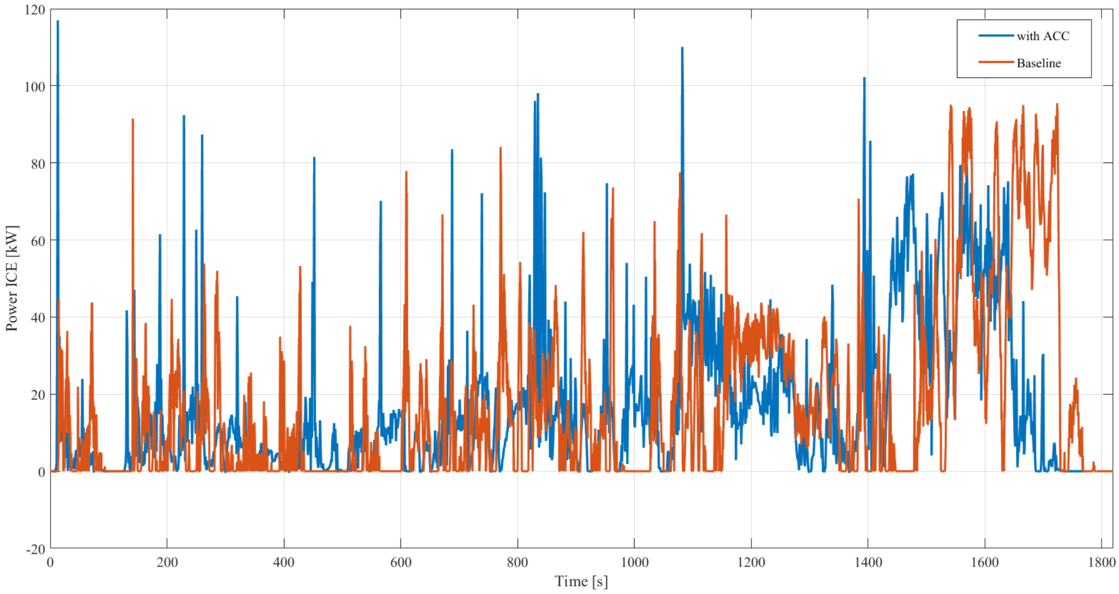


Figure 5.17: Engine power for the baseline (orange) vs. engine power for the ACC case (blue)

Collecting all the results from the different cases that have been tested, it is clear how the use of a hybrid configuration with the ECMS algorithm has an overall improvement in the fuel economy of the vehicle. From the fuel consumption values it is possible to see how the presence of the electric motor leads to an improvement of 6.2% with respect to this model with the ICE only (see tables 5.16 and 5.17).

As a final analysis over the results we can consider two different steps: the hybridization of the vehicle with no ADAS information which leads to a 6.2% of improvement, and the automation of the vehicle and so the addition of ADAS information to the hybridized vehicle, which leads to a further 9.1% of improvement in fuel economy. The high percentage of final improvement is the result of a different longitudinal dynamics of the vehicle and a different use of the electric machine. So, the final version of the model (P1 HEV with ADAS) accounts for a 9.12% of improvement, of which 4.55% is given by the energy component (see table 5.17) and the remaining percentage is the result of the improved speed profile.

Fuel consumption comparison	
P1 HEV no ADAS	10.30 [l/100km]
ICE only no ADAS	10.98 [l/100km]
6.20 % of improvement using the P1 HEV with the ECMS	

Table 5.16: Fuel consumption comparison

ADAS Fuel consumption comparison	
P1 HEV with ADAS	9.36 [l/100km]
ICE only with ADAS	9.807 [l/100km]
4.55 % of improvement in using the ACC with the ECMS	

Table 5.17: ADAS Fuel consumption comparison

Chapter 6

Conclusion

This final chapter wants to summarize the goals defining this project, the methods used and the final results achieved for each task, exploiting the possible future improvements.

The main goal to achieve was the minimization of the CO2 emissions and fuel consumption of the vehicle. The vehicle in question is a light-duty mild-hybrid electric vehicle modelled with a forward approach in a parallel hybrid configuration with the electric motor in the P1 position.

In this context, a simulation environment in Matlab/Simulink has been created to validate the functioning of both high level and low level controllers integrated in the model.
The high level controller implemented for the purpose uses an Adaptive Cruise Control logic to have a real time forecast of what the vehicle is going to do. The main concept of an ACC (Adaptive Cruise Control) is the ability of the considered vehicle (ego vehicle) to follow an other vehicle in front of it (the lead vehicle), knowing in advance, thanks to the use of sensors, what the behaviour of the lead vehicle will be. To do so, a scenario for the lead vehicle, representing the WLTC cycle, has been created through the use of the Driving Scenario Designer toolbox. The ego vehicle follows the WLTC cycle travelled by the lead vehicle and creates a new speed profile based on a set of rules. The ACC logic aims at maintaining a certain distance (the D_{safe}) between the two vehicles, which is calculated through the use of a camera and a radar. When the relative distance between the two vehicles is lower than the safety distance, the ego vehicle slows down to keep the safety distance, while in the opposite case, if the relative distance is too big, the vehicle accelerates until reaching a pre-set velocity defined beforehand. The maintenance of a specific distance between the two vehicles is regulated through the use of parameters, specifically, time (T_{gap}) and distance (D_{default}) parameters.

After a deep analysis over different parts of the WLTC cycle, a rule-based logic has been defined, where the time gap and default spacing parameters change depending on specific intervals of time. The intervals of time are selected accordingly to the driving conditions the vehicle is undergoing (Low, Medium, High and Extra High speed).

The rule-based logic for the ACC has been tested for two cases: in the case of the hybridized vehicle in P1 configuration with the support of an ECMS algorithm, and in the case of the non-hybridized vehicle where the only source of energy is the internal combustion engine.
In the first case, P1 HEV with ACC, two phases of the cycle have been studied separately before studying the entire driving cycle. The above mentioned parameters have been tested over a urban cycle and an extra urban one in order to find the best combination of values for the time gap and default spacing. The outcome of the experimental tests showed a 14.78 % reduction of fuel consumption for the urban phase of the cycle and a 16.83 % reduction for the extra urban cycle. Expanding the analysis over the entire driving cycle, it is possible to see an improvement in fuel economy of 9.12 % with respect to the P1 HEV model without the presence of ADAS information. Looking at the energy balances of the different cases, it is possible to see a lower use of electric energy from the model with the ACC, which implies that this improvement in fuel economy was mainly given by a smoother speed profile which avoids acceleration and deceleration peaks.
In the second case (ICE only), using the same parameters as for the previous case, an improvement in fuel economy of 10.69 % is registered when using the Adaptive Cruise Control logic.
From this results it is possible to see how a logic with a time preview can positively affect the fuel consumption of a vehicle. It is clear how a high improvement in fuel economy is also given by the hybridization of the vehicle without considering the high-level controller (6.2% of improvement in fuel economy). The higher percentage of improvement given by the ICE only case, is based on the fact that the fuel consumption of the baseline is higher than the one which considers a hybrid configuration (10.98 l/100km for the ICE only, 9.30 l/100km for the P1 HEV).
After this analysis of possible conditions it is possible to say that the best result in terms of fuel economy improvement is given by the combination of both the ECMS algorithm and ADAS information, given in this case, by the ACC logic. In particular, the improvement given by the ACC is represented by a further improvement of 5% compared to hybridization alone.

6.1 Future improvements

A further research on the optimal time gap and default spacing parameters could lead to an ulterior improvement in fuel economy, moreover, since a deep study was done only over the urban and extra urban phases of the WLTC cycle, other phases of the cycle, such as middle and high speed, could be studied to minimize the fuel consumption. The controller could be tested over different cycles such as the RDE cycle which represents the behaviour of a vehicle in real traffic conditions with no strict driving rules.

The study case to implement the control logic for this thesis project has been a moving vehicle to follow, depending on certain rules. The choice of following a vehicle was carried out with the idea of implementing an Adaptive Cruise Control logic but en other study could be done over static objects such as traffic lights, road signs or even pedestrians crossing the street.

The study operated in this project takes in consideration only the longitudinal dynamics of the vehicle and considers the vehicle travelling in a flat road. A further improvement could be the adaptation of the logic to a curved road or to a sloping street to see the actual behaviour of the vehicle in all possible conditions.
The ACC logic could be replaced, for a future study, with a different high-level control logic such as a Lane Keeping Assist System (LKAS) or a Traffic Jam Assist (TJA) to highlight the differences in the different strategies and to find additional improvements in fuel consumption and CO_2 emissions or for other purposes.

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