Università Politecnica delle Marche
Scuola di Dottorato di Ricerca in Scienze dell'Ingegneria
Curriculum in Ingegneria informatica, gestionale e dell'automazione
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Study of intelligent test bench for development and project of electric systems for traction of innovative vehicle

Ph.D. Dissertation of:

Marika Fanesi

Advisor:

Prof. David Scaradozzi

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XIX edition - new series

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Abstract

In the recent years the automotive industry requests, even more, the possibility to perform laboratory tests on prototype vehicles by using real operating conditions. Driven from the automotive market, the electrification of the vehicles cars has taken a significant role.

The scope of this thesis is to presents innovative techniques and methodologies applied both to electric vehicle and the testbench: the combination of the dynamic vehicle model with the entire testbench system allows to reach better performance and improve accuracy on real estimated electric vehicles performance. The experimental characterization of the electric motor and the engine is presented together with the real-life phenomena influencing the overall system.

The results have been tested in two different use cases: the complete model of a Mild Hybrid Electric Vehicle and non-linear model of a testbench system. The former use case is a linear model where the dynamic and steady-state are modelled, including the influence of external disturbance and noise. With this approach is possible evaluating different control techniques and introduce real GPS sensor data to verify the precision of the model. Two control strategies have been analysed, implemented and compared. The latter use case is a non-linear testbench model that integrates the first use case extending the application environment and using an innovative approach. This approach applied to the system is the Engine-in-the-loop. The choice to use a complex system requests a strong advanced control strategy. For this reason, the Adaptive Model Predictive Control is implemented.

Both use cases are verified and validated using standard driving cycles and evaluated through the emission value in terms of carbon dioxide calculated from fuel consumption.

These studies have confirmed the possibility of the system to achieve good performance in cases of real application; in this way the engine can be tested

in real-time with a vehicle model, or with the innovative test bench system, and inserted into the real process, achieving the scope of the research.

Abstract

Negli ultimi anni l'industria automobilistica richiede, sempre di più, la possibilità di testare prototipi di veicoli in condizioni operative reali. Spinta dal mercato automobilistico, l'elettrificazione dei veicoli ha assunto un ruolo significativo. Questa tesi presenta tecniche e metodologie innovative applicate al veicolo elettrico e al banco di test. La combinazione del modello dinamico del veicolo con l'intero sistema del banco di prova consente di raggiungere elevate prestazioni e migliorarne la precisione. La caratterizzazione sperimentale del motore elettrico e del motore endotermico viene presentata insieme ai fenomeni fisici reali che influenzano il sistema complessivo. I risultati sono stati testati in due diversi casi d'uso: il modello completo di un veicolo elettrico ibrido e il modello non lineare di un sistema banco di test.

Il primo caso d'uso è un modello lineare in cui sono modellati la statica e la dinamica includendo l'influenza di disturbi e rumore esterni. Con questo approccio è possibile valutare diverse tecniche di controllo e introdurre dati reali del sensore GPS per verificare la precisione del modello. Sono state analizzate, implementate e confrontate due strategie di controllo.

Il secondo caso d'uso è un modello non lineare di un banco di test che integra il primo caso d'uso estendendone l'ambiente applicativo e utilizzando un approccio innovativo. Questo approccio applicato al sistema è l'Engine-in-the-loop. La scelta di utilizzare un sistema complesso richiede una forte strategia di controllo avanzata. Per questo motivo è stato implementato l'Adaptive Model Predictive Controller.

Entrambi i casi d'uso vengono verificati e validati utilizzando i cicli di guida standard e valutati attraverso il valore di emissione in termini di anidride carbonica calcolata a partire dal consumo di carburante.

Questi studi hanno confermato le possibilità del sistema di raggiungere buone prestazioni in casi di applicazione reale; in questo modo il motore può essere testato in real-time con su un modello del veicolo, o con l'innovativo sistema del banco di test, e inserito nel processo reale, scopo della ricerca.

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Abbreviations

ABS	Agent-Based Simulation
AMPC	Adaptive Model Predictive Control
ANOVA	Analysis Of Variance
BEV	Battery Electric Vehicle
BSG	Belt-Driven Starter Generator
CO2	Carbon Dioxide
CPS	Cyber Physical System
CSFs	Critical Success Factors
DC	Direct Current
DES	Discrete-Event Simulation
DSM	Dynamometer System
DUT	Device Under Test
EGM96	Earth Gravitational Model
EiL	Engine-In-The-Loop
EM	Electric Motor
EMF	Electromotive Force
EU	European Union
EUDC	Extra-Urban Driving Cycle
EV	Electric Vehicle
FMEA	Failure Modes and Effects Analysis
FTP	Federal Test Procedure
GPS	Global Positioning System
GRR	Gage Repeatability and Reproducibility
HEMS	Home Energy Management System
HEV	Hybrid Electric Vehicle
HF	Hybridization Factor
HIL	Hardware-In-The-Loop
HWFET	Highway Fuel Economy Test
ICE	Internal Combustion Engine
ICU	Intelligent Control Unit
IM	Induction Motor
JP	Japanese
KF	Kalman Filter
KPI	Key Performance Indicator
LS	Least Square
LSA	Least Square Algorithm
M&S	Modelling and Simulation
MHEV	Mild Hybrid Electric Vehicle

MIL	Model-In-The-Loop
MIMO	Multiple Input, Multiple Output
MPC	Model Predictive Controller
MUT	Motor Under Test
NEDC	New European Driving Cycle
NOx	Nitrogen Oxides
OEMs	Original Equipment Manufacturers
PID	Proportional Integral Derivative
PIL	Process-In-The-Loop
R&R	Repeatability & Reproducibility
RCP	Rapid Control Prototyping
RDE	Real Driving Emission
SIL	Software-In-The-Loop
SISO	Single Input, Single Output
SOC	State Of Charge
UDC	Urban Driving Cycles
UI	User Interface
UNFCCC	United Nations Framework Convention on Climate Change
WLTP	Worldwide Harmonized Light Vehicles Test Procedure
XiL	X-In-The-Loop

Introduction

A brief introduction is given in this chapter starting from the general problem in order to outline the path followed. The second part give an overview of the PhD research and describes the activities in detail.

Problem Statement

In recent years, the automotive industry has strongly grown. To preserve the environment, during last years Governments have led to limitations on carbon dioxide emissions; these limitations are more severe every year, in that the transportation sector is responsible for over 20% of total emission in the world. This is a significant portion that includes road, rail, air and marine. Focusing on road, the cars' emission is around 14%. In EU there are an average of 1.7 people per car, and for that, the emission reduction is closely related to the efficiency and optimization of the vehicles and fuel used.
For all this reasons, the use of new technologies in automotive is a significant opportunity for industries and most of the companies for trying to adapt existing technology to grow, introducing new techniques. The research is strongly connected with the application in the industries that have a fast and dynamic market. Year over year regulatory pressure and restrictions on ICE-based vehicles continuing to climb, trends are indicative of an ongoing growth in the adoption of these alternative powertrains.
The introduction of new components considered in research as being able to meet market needs quicker. In this scenario, the introduction of electric motor as powertrain is an interesting answer. The main challenge consists to consider the different environments and to cover every part of use-cases. In that use-cases, Electric Motor (EM), a new type of machine that is a significant factor in the electrification process, is introduced. The automotive company needs to be ready to digitalize information and change the mobility idea. Electric and hybrid vehicles are part of the change. A new branch is opened and bring in the companies a new prospect and encourage a new vision. The use of electric motor, compared with traditional engine, presents some advantage as higher efficiency, lower emissions, lower fuel economy,

higher durability, and higher reliability and in this change, the test benches and the test runs need to be actualized. The higher efficiency is the first impact factor: this cause the increasing of performance of the overall system, while emissions are strongly reduced. Using the electric motor, the vehicle life increase, and the control unit in the vehicle easily integrate automatic control features. Other aspects that influence the performance are the energy sources, the type of batteries, the transmission, the converters, the motor type and entire configuration of the vehicle. The techniques and the methods applied on models and controllers depend on vehicles configuration and in the scientific community, the study is focused and based on specific categories and configurations. In the EVs there are more specific configuration: the power of the EM, the design and power of motor, energy system and power transmission generate different classes of EV. The most interesting EV is the Mild Hybrid Electric Vehicle (MHEV) because of the type of EM, its fast implementation in the production process, the electrical power available, the limitation of the fuel consumption and the possible functions performed.
To classify the different configurations, the value considered related to MHEV is the hybridization factor. The hybridization factor (HF) is used to verify the simulations and express the quantity of power provided by the electric part versus the total employed, giving a view of the dynamic performance of the vehicle:

$$HF = \frac{P_{EM}}{P_{EM}+P_{ICE}} \qquad (1)$$

where P_{EM} is the Power of electric motor and P_{ICE} is the power of ICE (Internal Combustion Engine).
MHEV also presents some issues. Firstly, the integration with the existing components as the issue regarding the integration with the Internal Combustion Engine, the costs related to upgrading the test benches, integration and change of configuration, battery packages and control units. Due to this transformation, the control strategies applied until now have been revised and modified to adapt them to the new systems. The controllers are significantly depended from the models, in particular from the accuracy. For this purpose, the metrics are essential to evaluated and predict the behaviour of the systems. The metrics to consider are the accuracy, effectiveness costs and efficiency. In some case, the EMs are prototype where the modelling is too costly, and the behaviour is unknown. In this situation where prediction

is difficult and tests are needed, a new approach is used. Among other motor study and development techniques, researchers and industry have introduced the XiL approach (X-in-the-Loop). An extension of the HIL and XIL approaches is a new method applied on testbench called Engine-in-the-loop. Engine-in-the-loop technique makes it possible to run the modelled testbench with an ICE with the same condition as when the engine is mounted in the real vehicle. EIL is focused on vehicle simulation. In this approach, a physical control unit and the engine is coupled with a model of the car and driver. The virtualization includes a testbench with high power and low inertia dynamometer that perform powertrain control development and vehicle emission evaluation. To improve the efficiency of the tests in general and in the testbench, the simulation and the control of the induction motor (IM) is important, and its parametric model must be fully identified. Engine-in-the-loop is widely used to ensure accuracy on testbench. Good identification of the IM is necessary for the overall model. The effects of the control applied on the whole system, depending on the model accuracy so the highly non-linear behaviour of the IM must be considered. The partial linearization of the motor helps to define real non-linear behaviour. Generally, this phenomenon is described and controlled using techniques to achieve results that are more precise. Considering the testbench, another improvement added to guarantee low emission is the integration of data from real sensors as GPS and accelerometers in that the environment is a part of these systems. Based on the data from the GPS sensor and measuring the position of the car, embedded controllers could better understand the dynamical position of the vehicle and compute the action to apply. The integration of GPS sensor into the control loop could help for tracking and managing the vehicle, but an accurate simulator is needed to design the complete control strategy. The precision of the new sensors distributed inside the cars has made it possible to extend the information available from the vehicle dynamics and guarantee better performance, maintaining the focus on the reducing of the emissions control system for the integration of GPS data and compensation of noise from the road on the vehicle. This allows to have more realistic emission and combining the sensors with the EiL approach in the testbench, could be reach interesting results. The final focus remains the emission value that is a critical issue, and for this reason, the various scenarios are detailed and include the different behaviour based on the type of road and the comparison of simulation data with real.

The last, but not the least factor to be considered is the dynamic and fast change in the automotive industries: the architectures changing every day and fusion, integration and sharing are the functions that needs to be included in the testbench. From digital twins to improve the behaviour simulation, the automotive company need to be ready to digitalize information and change the mobility idea. The information will be in-vehicles and on-vehicles. The interaction from the different sensors, the vehicles and the environment are agile-based with an intelligent-automated adaptive change. Some technologies are involved to predict the behaviour and estimate accuracy. On physical system is required the increasing demand of agility, flexibility, and low-cost implementation. The results are used not only to improve the quality of measurements but also to accelerate the business transformation. The new intelligent sensors and the managing services and infrastructure require new approaches to deliver the full potential transformation of automotive companies.

Thesis activities and overview

The PhD research has begun with the collaboration of the Università Politecnica delle Marche and the company ‘’Loccioni Group’’. The aims of this thesis are the study and development of the electric vehicle to optimize processes and to increase efficiency, and the modelling and control of an intelligent EIL testbench to have more accurate tests of electric motors and engine in order to increase the integration of these motors in the vehicles. The main validation criteria is the emission reduction. The testbench runs different tests based on the type of motor and in this thesis are developed tests for Electric motors and the engine. The main activities explained in this thesis are:

- Analysis and development of new technology (EIL) applied on testbench models and relative control strategies.
- Study and development of the virtual electric vehicle to reduce emission.
- Implementation and validation of these models on a case study integrating standard driving cycles and GPS sensor.

At this point, the choice of the configuration of the electric vehicle is significantly and results essential to clarify how it works. Based on the environment and the different conditions that can occur, there are two important use cases: the former is the electric vehicle that has to be modelled and analysed to understand the dynamic behaviour in a virtual environment that include real-life conditions. The latter is a non-linear testbench model where two critical features are included: the use of X-In-the-Loop method and the advanced control strategies. Actually, the XiL method is an interesting technology use in automotive to allow the collaboration of real components as hardware, software, real engine and the real-time simulations, maintaining the reliability and the efficiency of the system. This test with the XiL method allows the functional validation of automotive control systems. In order to evaluate both models work in the real environment, the simulations are integrated with real driving cycles data from the GPS sensor. The outcomes from these simulations lead to outline the fuel consumptions. To better understand the means of the fuel consumed value, the emission is calculated and compared with the limit defined by Governments.

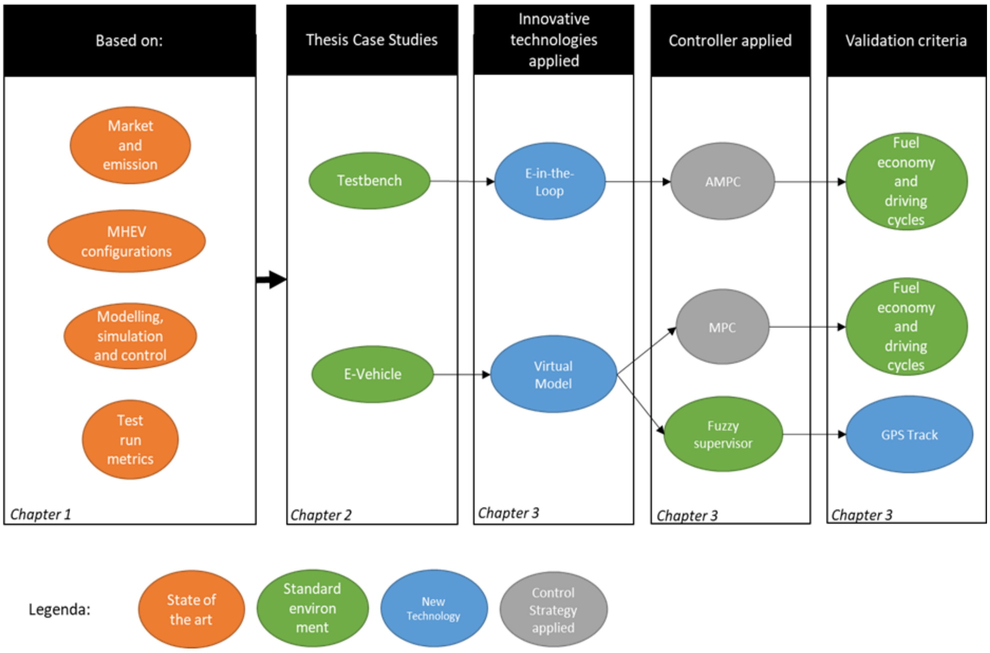

Figure 1 – Thesis workflow

In this section, the path of the research has been discussed. This can give an overview about the environment and methods needed to overcome the limits of the current test bench. In order to improve this limits, the EIL technology is studied and applied with advanced control strategy. In this way, the test bench will be more performing, increasing the rejection of disturbances and noises.
This thesis is organised as follow: the Section 1 presents the background considered, including the limitations regarding the emission and the business companies' analysis that bring to the electrification process. An overview of modelling and simulation techniques and test runs metrics complete the paragraph. Based on state of the art, Section 2 describe the components, technologies and methods chosen in the simulations. Section 3 shows two case studies: the first one regards development of vehicle's modelling, control and simulation of an electric vehicle; the second one describes the non-linear testbench model and the XiL method applied. The control techniques change with the case study. The former starts with a PID controller and follow different directions: an increasing of accuracy with the Model Predictive Controller and a faster response with a fuzzy logic supervisor. The latter design an advanced control technique called Adaptive Model Predictive Control. Both standard driving cycles used by Governments and driving cycles based on GPS tracks from the real world are applied to define the reliability and the validation of the entire system. Finally, in the Section 4, the conclusions are drawn.

Chapter 1. State of the art and background

This thesis is based on a strong background concerning vehicles emission that has guided the electrification process and created different electric configurations. To reduce costs, vehicles modelling and control are developed and fast implemented. The test run metrics are fundamental to verify the entire system and confirm the validation of the system.

1.1. Market and emission

In the last decade the automotive market has enormously grown. The major segment includes commercial vehicles and passenger cars. Due to the recent COVID-19 pandemic, the market has undergone a big change: from the sales channel to the production line, the cars are in overproduction and the storage of produced cars is full. The impact has been severe, and actually the global market is under pressure. Automotive industries have a great importance and in some countries are fundamental. In this scenario the attention for the electric vehicles is increased in particular for hybrid vehicles. Governments across the globe are providing support on the purchase of electric vehicles to solve the environmental issues arising due to pollution from conventional cars [1]. Especially in Europe, the automotive industry chooses a specific direction. Since 2007 the companies decide to progressively invest and record a great profit. In 2012 profits have suffered losses derived from two issues. that have caused a market decline. These two reasons were: firstly, the limited number of new car sales and, consequently, the overcapacity in industries; secondly, the aggressive competition in the pricing of the new cars. At the other hand, the automotive market is global and other parts of the world need to be considered [2,3]. China, Japan and the US are emerging markets and export and product a significant amount of car sales. Profits are projected to grow more than three times as fast as in well-known markets. This challenge is hampered by the total investments required for new powertrain technologies. The main actor in this scenario are the Original Equipment Manufacturers (OEMs), define as companies that manufacture and market

components for other companies that assemble them to finalize a product to sell. Where the market sees a challenge, sometimes for OEMs is an opportunity. The industry changes in some important ways: new policies and regulations are introduced to limit the market, and the differentiation of the various customers depend by the country. However, these practices are clear and keep the market stable. As the production, the development and implementation of new feature demand is regulated, and only the management of the efficiency and quality helps to increase profits [4-6].
Sales in the automotive industry is marked by steady growth, and this has a significant impact on the market. At the other hand this increase the emission and the effects on humans and the environment. The emission limit is stricter, and the object is a strongly CO_2 reduction. As explained in the introduction, in the MHEV the use of the electric motor combining to the engine helps to maintain the performance and add the key value of lower emission [7,8]. However, the challenges in the market represent a fundamental innovation to restart and transform the forced change in an opportunity. The main challenges are:

- Complexity and costs reduction: the governments boost the respect to the environment and the implementation of active safety requests higher costs and complexity. The additional services derived from the different market segments and related to the vehicles increase complexity. Besides, the complexity, responding to the demand of buyers, requests to add new features and this extends the platform used. The increasing development of unique easily integrated traits answer to these demands and encourage the use of new technologies.
- Different markets: the market, in general, has some segments that significantly differ, and the location and production can change future sales. Adaption and change are the primary value in industries.
- Virtualization process: the demand is to digitalize the vehicles and, in general, all the process. The driving experience is a resource that includes ease of use, connectivity and information sharing, communication and interaction with the environment.
- Industries landscape: the management of the companies and the innovative solutions need to match the customers’ demand. Above all, competition is emerging.

Challenges are dependent and interconnected each other; to capture future growth, strategic choice and appropriate investments and resources are essential. Moreover, the penetration of advanced technologies led to increasing regulatory pressure against vehicle emissions [9-12]. At the other hand, the industries are encouraged to improve their knowledge and significant invest in the research. Common target is the reduction of the emissions. Regarding that, as shown in fig. 2, the emission target is decreasing by about 20% from 1990. Traffic itself, as well as energy supply for transportation performance, have a great impact on the environment, as they cause emissions, noise pollutants and resources use.

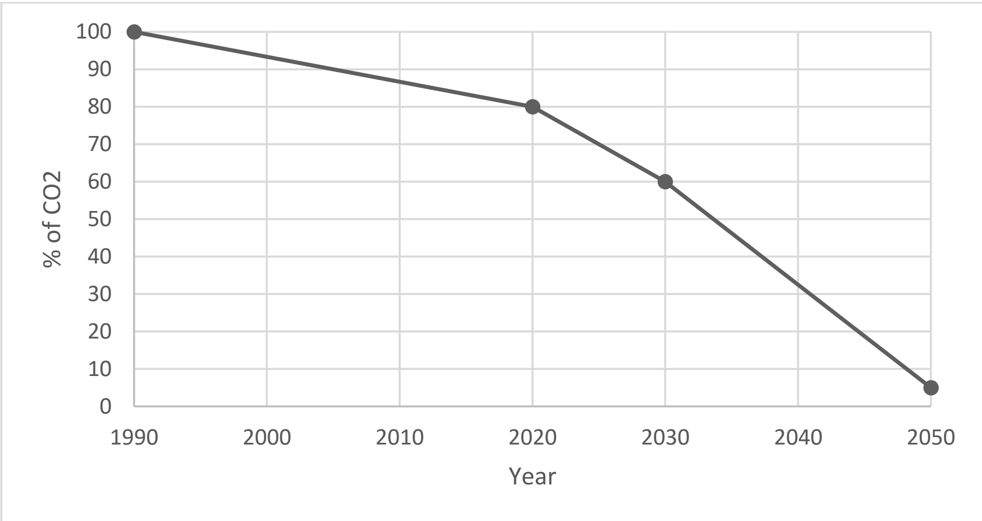

Figure 2 - Emission target

Emissions are mainly caused by transportation. In particular, the CO_2 emission promotes the greenhouse effect, mainly caused by burning fossil fuels. Reducing emissions is a central target of Europe, and the policy tools used to achieve this target is to set a range that reflects the economy. The industries need an intensive economy grow to reach this target. However, the limit emission, compared with the business strategies, is not always aligned, and this represents an excellent effort for companies that have to change by adapting to local legislation [13-15]. In fact, in addition to the EU targets,

Member States of Europe are also obliged to meet annual emissions targets or so-called interim targets. However, talking about the death of the ICE is premature. The technologies adopted and creative solutions have allowed performing a significant impact.
The energy demand of a vehicle is defined in the test cycles [18]. The respective energy demand, fuel consumption and CO_2 emissions in the vehicle with ICE depend on driving style, route, road, traffic, type of vehicle and environment. They may differ, and the value of consumption change significantly.

1.2. Mild Hybrid Electric Vehicles configurations

The evolution of the technologies has changed the scenario and the requirements. These requirements have led the industries to look for alternative approaches. An hybrid vehicle consists of two different energy converters and two different type of energy storage, used combined for propulsion task [19,20].

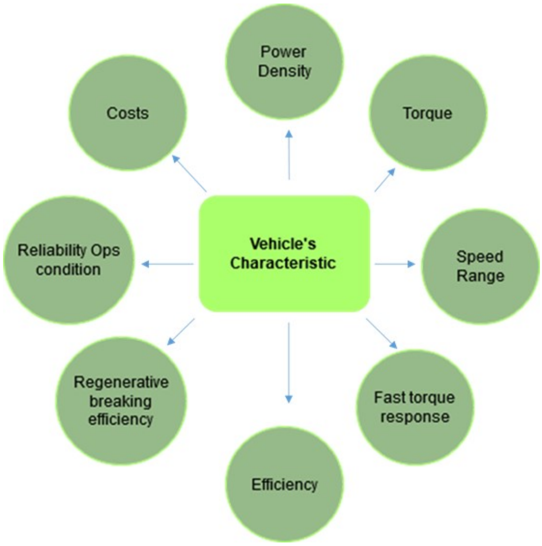

Figure 3 - Vehicle's features

The vehicles produced can be subdivided based on their components and differs for:

- Power density: is an important value that represents the amount of power per unit volume. It includes time rate of energy transfer, and it is referred to the internal capacity of the motor;
- Torque: it is the measure of rotational effort applied on engine crankshaft or the driving force in an electric motor;

- Speed range: it is the minimum rated speed of the motor at which it produces its minimum rated power when the specified voltage is given at its rated load. The maximum speed is the full attainable speed in a motor;
- Fast torque response: according to load torque and mains supply, this is a torque response on the mechanical system;
- Efficiency of speed and torque: based on the input and output speed and torque, the efficiency is a value that expresses the weight of the losses in the system;
- Regenerative braking efficiency: it is a force derivative to the comparison of the demanded brake torque and the motor torque available. In case of EV is the conversion of the vehicle's kinetic energy into chemical energy stored in the battery.
- Reliability of vehicle in operating conditions: reliability of a car is defined as the probability that the requirements of the operational conditions do not influence the performance of the system during the operating period. The reliability of each component including the configuration of the entire vehicle determines the system reliability;
- Costs: the reduction of costs is a strategy that includes the measurements of costs, the improvement of process and the optimization of the systems and their components.

These characteristics significantly influence the performance, and the MHEVs is distinctive for the two different energy pathways that contain: the liquid fuel-based and the electric-based propulsion. In addition, the battery is a component that affects the vehicle life, and it is an essential part of the MHEVs [21-24]. The recharging is a parameter on the analysis of an MHEV, and it is the central issue for industries nowadays [25-27]. The development of the battery, in general, could be applied in some fields like wind-solar energy generations [28-30], MHEV [31-33], engines [34-35], aerospace [36]. Additionally, the 48V electric motors could have some characteristics that influence the performance; this includes vibration behaviour, acoustic behaviour, thermal behaviour and recharging [37-39]. Engine, energy storage, mechanical transmission and powertrain control are the component of a traditional powertrain system. With the addition of an electric motor system, the traditional powertrain system grows into an hybrid powertrain system. The use of MHEV is principally driven by emission limits and targets of CO_2. The characteristics of MHEV are the functions that are available as electric torque assistance, regenerative braking, idle start-stop and electric drive. The idle function reduces fuel consumption, optimizes energy consumption and offers a better user-experience [40-41]. The torque request compensation is necessary with an internal combustion engine. Adding an electric motor, the torque can be modulated and split.

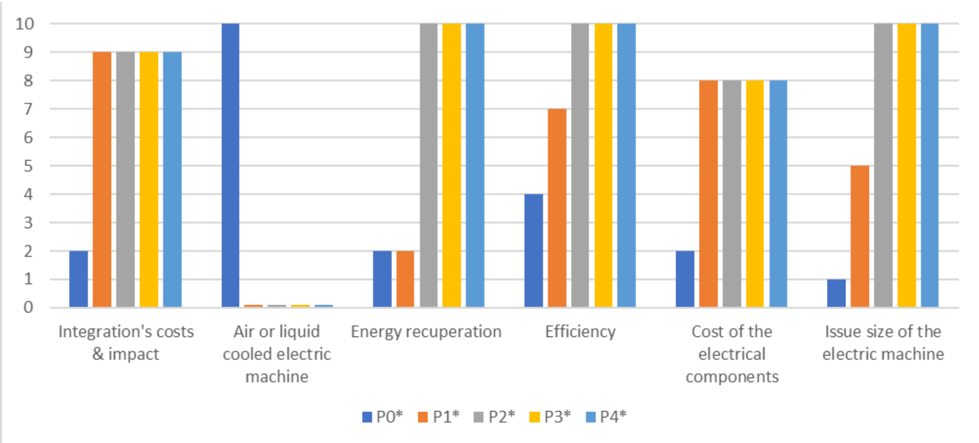

Figure 4 - Features P0, P1, P2, P3, P4

Another component includes in the MHEV is the generator that can be a belt-integrated starter generator or a crankshaft-integrated motor generator. The MHEVs differ in power and battery voltage based on the generator type. The configuration of MHEVs change depending on the position of components: this affects the efficiency of the overall system. The possible configurations are:

- Parallel-parallel;
- Series-series;
- Series-Parallel.

Serial hybrid vehicles have a connection of the energy conversion machines with a mechanical connection between the combustion engine and wheels.

The ICE drives the generator, which is connected to EM and battery. The setup of the working point depends on the engine map and is not configured statically. For parallel hybrid configuration, the ICE and EM are mechanically linked to the driven wheels.
In this case, the speed ratio is fixed, and the torque addition is a sum of the traction force and the torque ratio from both energy converters. In the parallel-series configuration, the power provided by the ICE is connected mechanically to the driven wheels. The total efficiency is higher than the other two types of configuration. The classification in series or parallels configurations are used to differentiate the type of EVs [42-46].
Another possible classification based on the place of EM are:

- P0: the ICE and EM are connected through a belt;
- P1: ICE and EM are linked directly through the crankshaft;
- P2: EM is link side or joined between the ICE and the transmission;
- P3: EM is attached through a gear mesh with the transmission, ICE and EM are decoupled;
- P4: the EM is on the rear axle of the EV; the electric engine is decoupled from ICE.

In the automotive industry, the technology exploited for built MHEVs is 48V P0 mild hybrid architecture. The results of these choices are reduction of CO_2 emissions, dynamic performance boost and low integration costs. The main difference from P1 and P0 is the presence of belt drive in advantage of P1 architecture. This caused an increase in the efficiency and higher electric machine torque in terms of amplitude and response. P1 architecture has not only advantages: this topology has higher costs and notable impact on the architecture of an existing vehicle. In the P3 mild hybrid configuration, the electric engine is linked on the transmission, on the output shaft. In the P4 configuration, the electric engine is set on the rear axle drive. The P4 configuration grants the vehicle four-wheel drive skills, with the front axle supported by an internal combustion engine and the rear axle supported by an electric motor. The P2, P3 or P4 Stop & Start function can be achieved with a standard starter. The characteristics of transmission integrating to the high-speed electric machine are dynamic performance, engine power between 26 – 65 kW, electric machine voltage between 48 V.

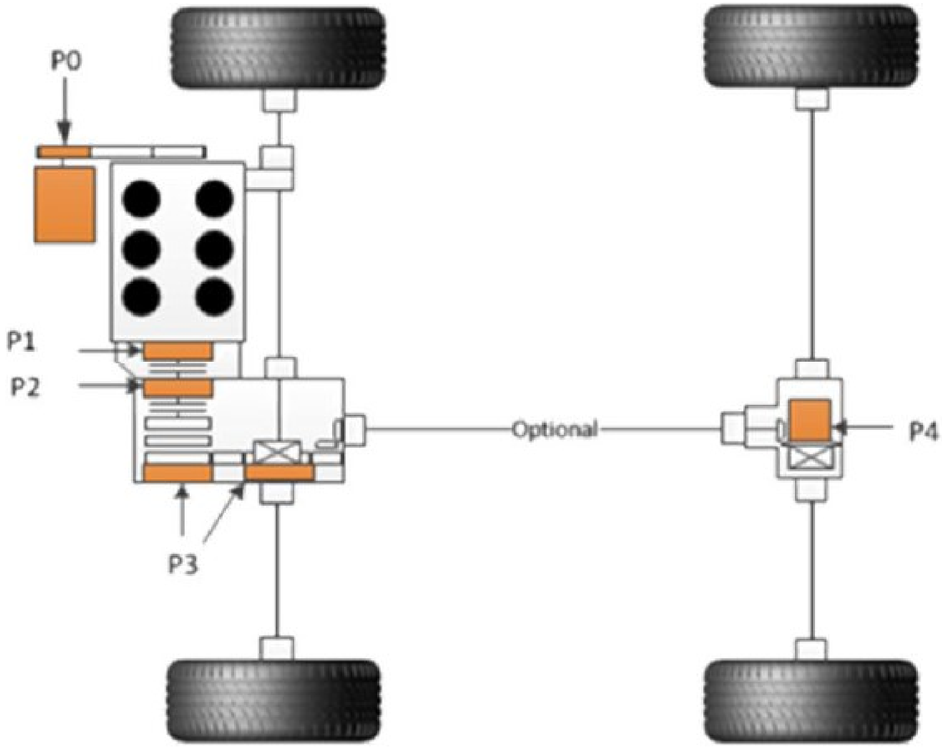

Figure 5 - P0-P4 Configurations

Table 1 - Architecture description P0-P4 configurations

Architecture	Description
P0	eMotor at Crank Shaft or Belt
P1	eMotor at Fly Wheel
P2	eMotor at the transmission input
P3	eMotor Integral to transmission
P4	eMotor at Rear Axle

The main aspects of being retained regarding MHEV architectures are that the first mild hybrid systems the electrification process saw the transition from the P1 configuration, immediately replaced by P0, P3 and P4. The P0 architecture is the one most used in MHEV, but the market will shift more towards P4 architecture. The hybrid functionality controls the grade of electrification.

1.3. Modelling, simulation and control

Last decade presents different studies of MHEVs from modelling, systems simulation, safety, reliability, fuel consumption points of view [47-50]. The models are of two types: linear and non-linear. The linear model helps to develop a plant with dynamic behaviour. The model is obtained through mathematical equations that describes the particular action based on physical laws [51-53]. The linear model can be design based on data processing that identifies the behaviour. The representation of the real world includes system dynamics modelling. The models are a multivariable system and based on numbers of input and output is defined MIMO (Multiple Input, Multiple Output) or SISO (Single Input, Single Output) in case of one direction model. Another type of linear model required a dataset of information, and the plant is assumed as a black box (e.g. [54]). The black box has some disadvantage: first of all, the model is focused on an operating point, and the validity of the model is limited to this. At the other hand, a model that have known global structured properties and a defined behaviour is called white box [55]. To identify the plant, the approaches possible is:

- Direct;
- Indirect.

The direct approach is a method that includes the stabilization in an operating point and the change of the signal around it. The indirect process consists of stabilization of the system in a closed loop and the identification of the system with input/output dataset. This dataset is fundamental to define the behaviour and the dynamics of the model.
Modelling process comprises some steps, as shown in figure 6; the identification is the first one.
After experiments and acquisition of the dataset, the structure of the model needs to be chosen. The parameters of the model are estimated through some analytic methods and the model must be evaluated. For the non-linear model, the strategies are to reduce the complexity of the system. The model can be linearized and compared with the real physical process. After the modelling, the system has to be simulated. This process requires to define the simulation method: an agent-based simulation (ABS) or a discrete-event simulation (DES).

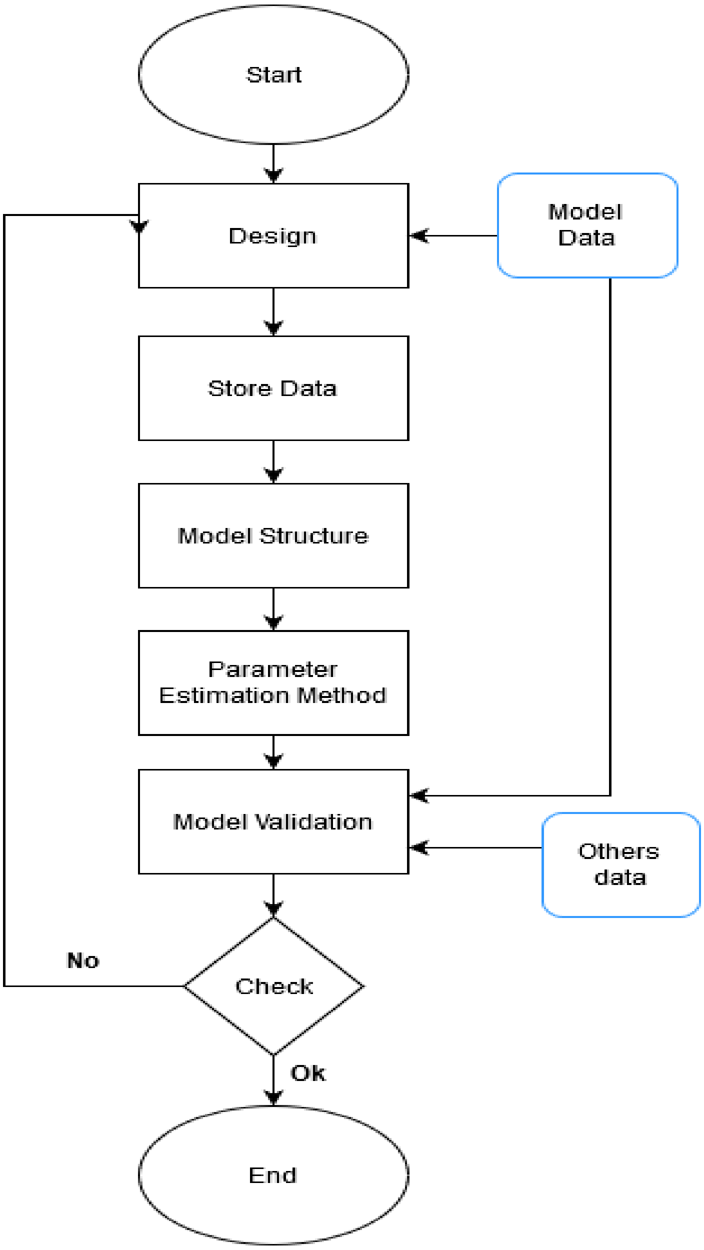

Figure 6 - Modelling process steps

This identifies a complex system where autonomous elements of the system with own goals and objectives interact with the environment. Besides, the set rules provide to define the different behaviour possible for every agent. The rules can also contain complex functions and agent roles. The latter is event-based and represent a structure where the set of states change instantaneously in time. Generally, these rules are a set of queues and tasks, including a start and an end event. This approach is entity-based and consider the single event to define the action. Entities represent some aspect of a system that passes through that system simulation, engaging in interdependent cycles of various activities [56]. The time is an important variable that influences the simulation: in DES depends by the next event, in ABS is stepped and the simulation advances in time increments executing its agents in each step. Another classification of simulation is a data-driven, physics-based and cyber-physical simulation. The data-driven simulation facility the process analysis in that contain information regarding process, layouts and data sources. The physics-based simulation includes the running of a linear model built on physical laws. This is possible when the behaviour of the system is linear and is built a linear model. To increase complexity and put the system in the real world the addition of disturbs and noises is recommended [57,58]. The simulation and, consequently, the system is represented as an hybrid model where some effects present in the real environment is studied.

In the case studies presented in Chapter 3 the modelling and simulation are entirely different. In facts in case of a vehicle, the most interesting parameters evaluable are the longitudinal dynamics, lateral dynamics, wheels and environment. Based on that, the vehicle model is based on physics laws, and it is modelled, implemented and simulated integrating the physical equations. On the other hand, in the case study regarding the tests on testbench, this is modelled and simulated with a linearized model. This choice is necessary in that the testbench is highly non-linear and is designed as a linear model of a low-pass filter with fast dynamics and include a simplified non-linear mathematical model of the device to test.

The case studies represent the opposite type of modelling and simulation (M&S). To presents the control strategies (e.g. figure 7) possible to apply on the systems, it is important to know that are strongly associated with the methods of M&S.

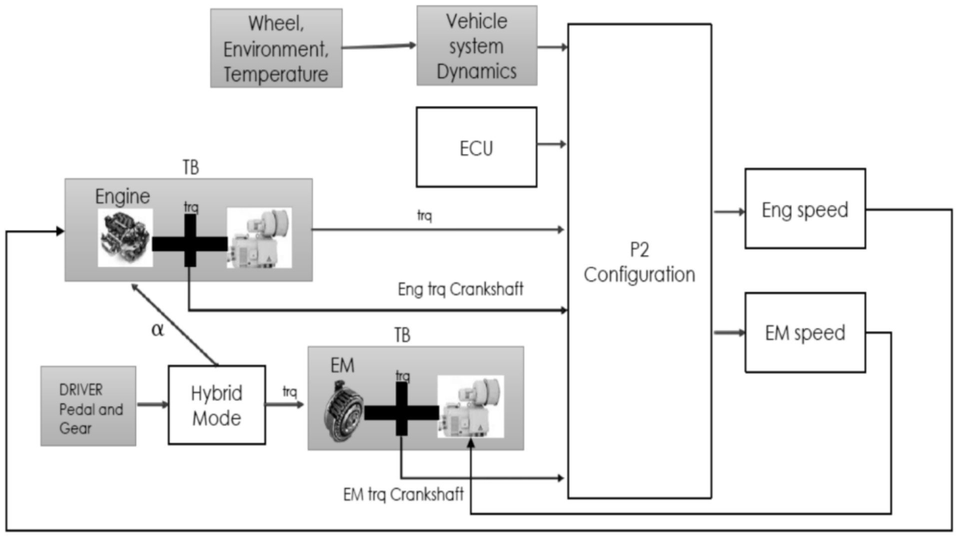

Figure 7 - Modelling and Simulation example case study

The control methods theory examined are:

- PID: Proportional Integral Derivative controller use to control process variables. The most accurate and stable controller;
- Fuzzy supervisor: is responsible for setting proper setpoints to the PID controllers;
- MPC: Model predictive control, an advanced method of process control that is used in a process with satisfying a set of constraints;
- AMPC: Adaptive MPC in which parameter estimation and control are performed online. The adaptive controllers adjust the prediction model at run time to compensate for nonlinear or time-varying plant characteristics;
- Sliding Mode: is a nonlinear control method that alters the dynamics of a nonlinear system by application of a discontinuous control signal that forces the procedure to follow a cross-section of the system's behaviour.

These are applied based on the system modelled. In this thesis, the control strategies considered are the closed-loop [59,60]. The elements that distinguish the closed-loop systems (figure 8) are:

- The reference input: is the desired value of the measured output. A suitable control method allows to reach that these values are closed;
- The control input: is a dynamically adjusting of parameters that define the behaviour of the target components of the system;
- The control error: is the difference between the reference input and the measured output;
- The computational of the controller: the value of the control input is influence by the current input value and the past error value;
- The disturbances and noise: are a change that affects the measured output;
- The measured output is the quantifiable amount of the target system.

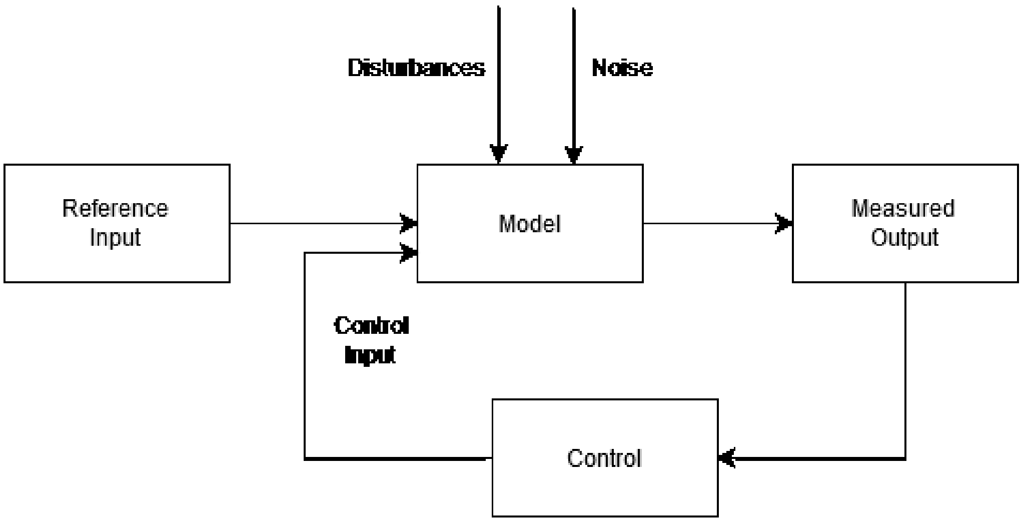

Figure 8 - Control schema

In general, there are multiple elements for every point presented. Not of all the point above are necessarily present in the system and the controller provide to achieve the objectives purposed. The most common points are:

- Regulatory control: this control guarantee that the reference input and the measured output are equivalent;

- Disturbance rejection: assure that the noise and disturbance present in the system does not influence the output measure, actin on the disturbance input;
- Optimization: the value of the measured output is gained optimizing the system and the time response.

In both case studies of Chapter 3, all of the above aims are treated. With these techniques, the system results stable and accurate without overshoot and converge to the steady-state value. The optimization problem is the most complete and significant task for the industries in that increase efficiency and performances of the entire system.

1.4. Test run metrics

Testing plays a fundamental role in the automotive industries. The Gage repeatability and reproducibility (GRR) tests have long been used to evaluate the usefulness of systems. The Gage R&R is a statistical tool that measures the influence of the difference that is deriving from the measurement of the tests and the people taking the tests [61-63]. These tests are a methodology that defines the difference in the measurement system and demonstrate the validity of the system and provide a simple approach to verify the process:

- Repeatability: measure the variation in measurements with the same testbench in the same conditions;
- Reproducibility: measures whether an entire study or experiment can be reproduced in its entirety.

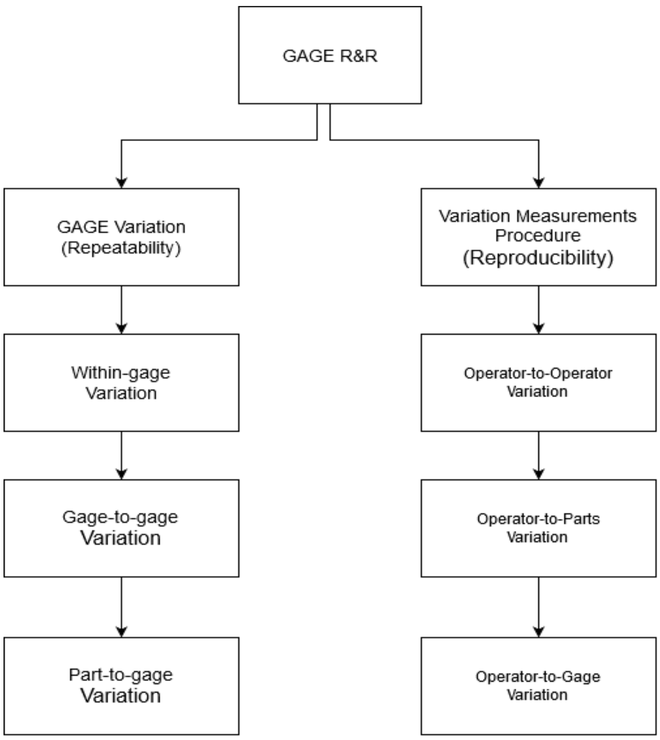

Figure 9 - Gage schema description

Tests help to define the quality of the measure [64]. The acceptance criteria include to evaluate the measuring range in percentage: when the Gage R&R is under 10% the measurement system is satisfactory; if the range is between 10% and 30% the measure can be accepted for some requests; when is over the 30% the measurements system is intolerable. Testing metrics are quantitative measures that help to estimate the progress, quality, and health of a software testing effort. A metric defines in quantitative terms the degree to which a system, system component, or process possesses a given attribute. The tests metrics are decisive, and the specific metrics are:

- Test coverage: is defined as a measure of the amount of testing performing by a set of tests;
- Test tracking: define the tests and their carried;
- Test efficiency: define the useful of the test and determine the defects and faults;
- Test effort: is an estimation that determines the weight of the tests;
- Defect distribution: helps to define the parts of the process most vulnerable to defects and faults;
- Test execution: measure the activity of tests and the results of these;
- Regression: this metric is useful to measure the defects introduced with change;
- Test economics metrics: quantify the economics parts to plan to budget;
- Unit test: tests the single part to assure the operation of every part;
- Integration test: after the unit test, this is needed to define the correct behaviour of the system and determine the proper run.
- Functional test: this includes the testing of every functionality presented in the define phase of the system;
- UI (User Interface) test: systematizes repetitive activities to guarantee critical interaction work.

These metrics are critical to defining the performance of the system and reliability. The test metrics are adopted to remain competitive on the market and integrate particular methodologies like Six Sigma and Lean Manufacturing [65-67]. The Six Sigma method measure the number of defects in the process, and analytically try to solve and delete issues. The metrics to consider during the development process are:

- Technology metrics: this metrics are defined as component and application metrics and consider the performance, availability and flexibility of these;
- Process metrics: determined by the measure of the Critical Success Factors and the Key Performance Indicators (CSFs and KPIs);
- Service metrics is the measure of end-to-end service performance.

The management of problems is integrated with the supply chain that combines supplier, costumers and business [68,69]. This integration leads to optimized results: the keys are quality, cost reduction and knowledge. Lean Six Sigma (LSS) approach in conjunction of principles and tools that aims elimination of process defects defined ‘‘Zero Defects’’ process. This approach is some phases:

- Define phase: in the first step the customer satisfaction and demand are considered, and it is called the requirements process;
- Measure phase: In this phase quantities and qualitative data is acquired to determine an exact current situation;
- Analyse phase: in this phase, the Six Sigma requests FMEA and various skills and the Lean Manufacturing approach is focused on time-saving and process efficiency techniques. Besides, ANOVA techniques are introduced to analyse the samples;
- Improve phase: the choices are decided in this phase: the issues and waste analysed are solved implementing the solution;
- Control phase: after improvements, the control phase allows to maintain the performance, report problems and minimizing waste.

The metrics included in the LSS are strategic to improve competitiveness and provide an easy structure with an optimized flow [70,71]. In this case, the integration of these metrics leads to increase quality, costs and business performance. Regarding the analyse phase, the FMEA and ANOVA techniques need to be studied in depth. About that, the FMEA is a step approach for recognising the possible fault in a design, a manufacturing process. For new processes, it identifies potential bottlenecks or unintended consequences prior to implementation. ANOVA is the analysis of variance, a statistical method that splits observed variance data into different components to use for additional tests. This approach is used for some groups of data to gain information about the relationship between the dependent and independent variables [72,73]. These two approaches are fundamentals to analyse and evaluate the entire process.

Chapter 2. Environments and methods

In this chapter are described the particular environments and the innovative methods used in the case studies presented in the next chapter. This step is fundamentals to understand better which situations and parts occur, and the integration and employment of every component. Hardware, software and technologies presented initially will be applied to different conditions differentiating the driving cycles to obtain the real fuel consumption.

2.1. Testbench

The main focus of this thesis is the testbench. Test benches have specific structure developed especially for the type of test that is performed and depends on the electric motor. The same testbench can be configured based on the type of EM or ICE under test. Testbench is a complex system that has the aim of carrying out measurements, with or without load, at room temperature, on the electric motor under test. Hardware components included in this system are:

- Dynamometer;
- Inverter;
- Battery Simulator;
- Torque meter;
- Device Under Test (DUT);
- Control Unit;
- Cast iron floor;
- Sensors.

Based on that, the three main components are the dynamometer (dyno), the inverters and the DUT. The dynamometer is the main motor in the testbed and has a well-known characteristic. The inverter offers high performance and highly flexible motor control to meet the different needs of machine manufacturers and the rigorous specifications of the most demanding

industrial applications [74-75]. The controller features full position feedback, and high-performance control of dynamic permanent magnet servomotors enhanced control with single and multi-axis network synchronization. The last part that is relevant for this type of applications is the Device Under Test in general, also called Motor Under Test (DUT or MUT) in case of an electric machine that has included own inverter [76].
The components depend on the configuration of the testbench that can be configured in three modes:

- Setup;
- Run Disconnected;
- Run Connected;

In the Setup Configuration, the mechanical chain is avoided, and the motors are enabled to enter in the running mode. The maximum speed and maximum torque are set and are unique for both motors. The Run Disconnected Configuration refers to the case in which it is necessary to test the operation of one of the two motors or both without the mechanical chain (joint-torque-joint) having been connected. In this case, for the operator, it is not possible to activate the torque control, to avoid sending the motors out of control, since no resistant torque is applied. For these reasons, there must be no interlock between Dyno and MUT because it may be necessary to operate only one of the two or both, but completely independently. In the Run Connected Configuration, the entire system is complete, including the mechanical chain and protections. All of the tests on the MUT are possible and enabled.
The configuration modes change the automatic part presents in the testbench and change the availability of the single hardware/software modules. Usually, the limitation forces in the mechanical chain in case of 48V electric motor DC are the maximum torque, maximum speed and maximum payload brake power. In case of the active load tests, the limitation derives from sensors. For example, the typical situation regards the torque meter. This is an active part in this case that bound this power to 44 kW. To avoid this limit is needed to change sensor; the power of the torque meter that can be increased up to 110 kW.

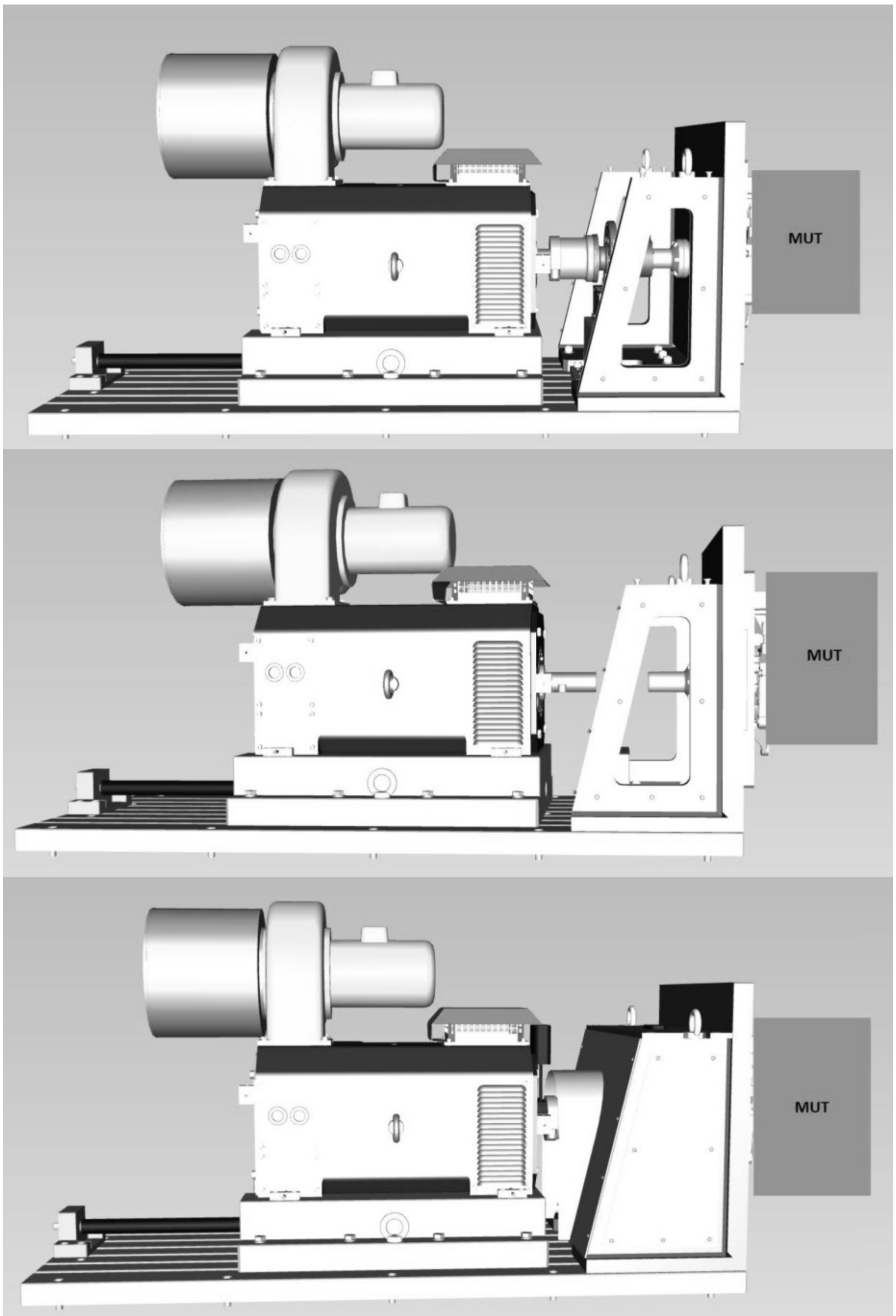

Figure 10 - Testbench configuration modes

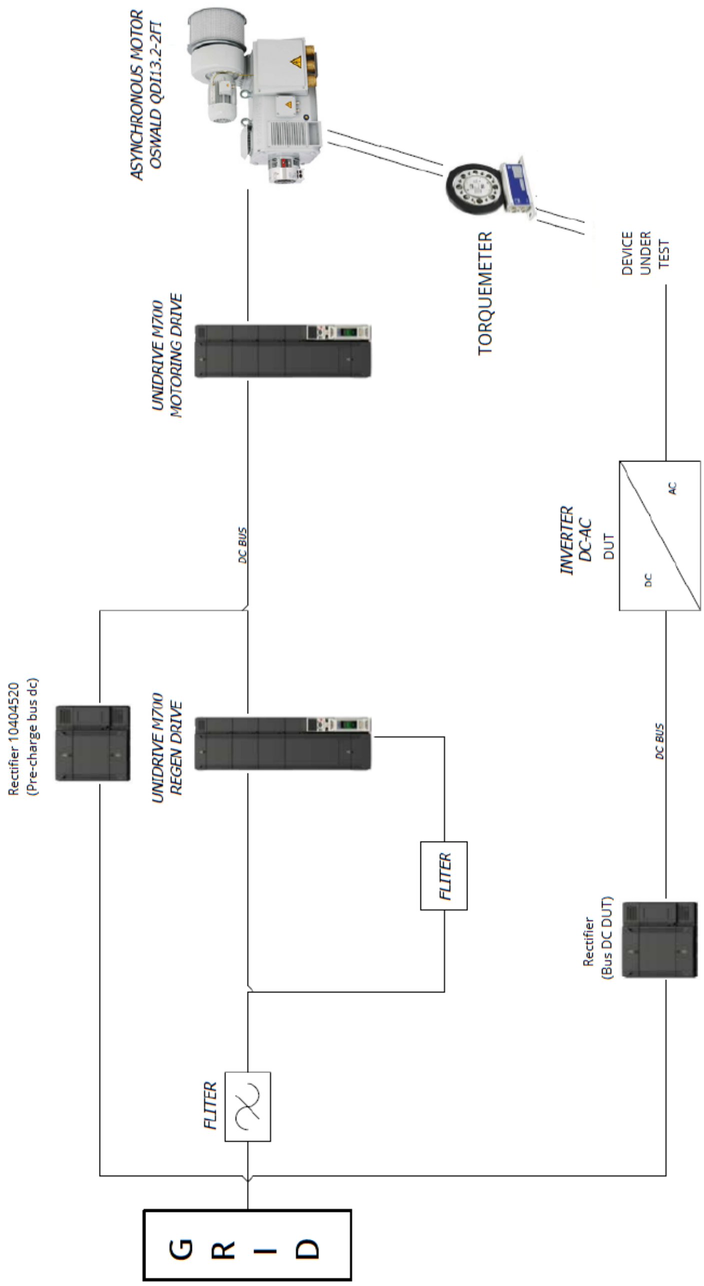

Figure 11 - Testbench connections

In figure 11 is shown the testbench connections, including hardware design and grid. In addition to the hardware parts and connections, the possible software controls are:

- Speed Control;
- Torque Control;
- Feedback Torque Control;

In the case of MHEVs the differentiation does not regard the configuration of the testbench. The test and, consequently, the conditions change adapting the parameters and the boundary considered. The battery storage capability technology and costs are a limit to the EV where they want to improve components efficiency, motor and the total system design [77-78]. In order to improve motor precision, intelligent control algorithms have been widely applied [79-80]. The main tests are executed to measure the electrical and mechanical parameters of the motor.
Furthermore, the design of the electric motor is validated by the test bench as outlined in [81]. With the sensor assimilate to test bench, there is also intelligent control unit. The ICU determine the specific time to synchronize the operation, and this is fundamental to obtain a reliable result. To reduce costs, the virtualization of some components and connection [82] or the share of components. The introduction of the cyber system in the intersection with the physical system has created the CPS paradigm [83]. The CPS paradigm combines engineering models and methods with computer science [84]. These techniques are spreading and their application is increasing in various sectors. In automotive CPS testbench detection, fusion and identification of sensors to improve safety and information about devices under test are known problem that is resolved with models and with cyber methods in terms of accuracy and precision [85-88]. CPS methods, models, concepts bring new technology, new infrastructure and new approaches that are the development of those already existing [89]. The disadvantage and limits of CPS are the determinism and the continuums of the physical world [90]. With the CPS approach the general system accuracy is guarantee [91]. This CPS vision could be integrated on MHEV to unleash all performance tests about the electric axial, electric motor and MHEVs. With CPS approach, the MHEV could control, be controlled and could be monitored the parameters of the EV to improve security and reliability.

2.2. X-in-the-Loop technology

Nowadays, new technology approaches have increased the field of testbench applications. The X-In-the-Loop (XIL) approach is one of these. To define X-in-the-loop is needed to define the concepts, the processes, the technologies and methods. The XIL consist of some different sub-phases or sub-category applied on use-cases. The aims are to obtain better results and improve performances integrating these new concepts. X-in-the-loop effectively introduced new classes of design concepts (fig. 12).

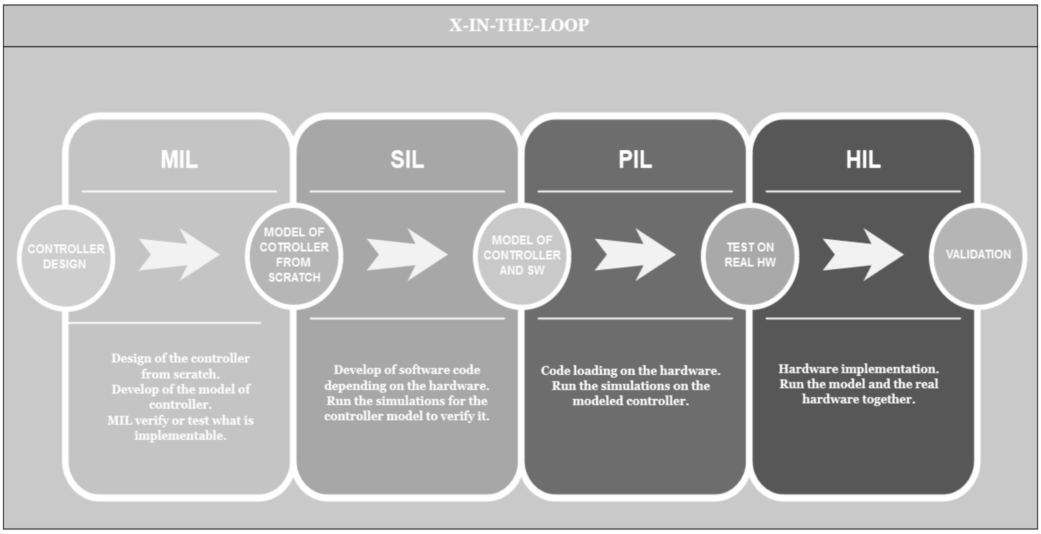

Figure 12 - XiL Design and concepts

The XIL is an integration of models, real and virtual environment limiting costs and allows to model all the variable in the system. The sub-phases that compose the XIL are:

- Model-in-the-loop: (MIL) is the first block used for the simulation in a purely virtual environment.
- Software-in-the-loop: (SIL) verify the model of the electronic control unit in a modelling environment to test the software.

- Process-in-the-loop: (PIL) is when the code developed is integrated into the real hardware [133].
- Hardware-in-the-loop: (HIL) at this phase, a part of the designed system is made and available to be integrated into the other simulated real-time part. This phase may constitute for some projects the only phase that is used. When the hardware is available, rapid control prototyping and testing is done with the real hardware. For complex systems, like an hybrid car power drive, the controller will be ready before the hardware it controls. HIL testing, where the real hardware is replaced by its RT digital model, is used for debugging and refining the controller.
- Engine-in-the-loop: (EIL) a new concept included in the HIL simulation that include a real engine in the system. This approach is used in this thesis to evolve the traditional testbench.

The block diagram-based model is automatically implemented in real-time through fast and automatic code generation; the prototyping and the iterative testing is, therefore, significantly accelerated [92]. HIL differs from pure real-time simulation using the "real" controller in the loop; this controller is connected to the system that is simulated by input/outputs devices.

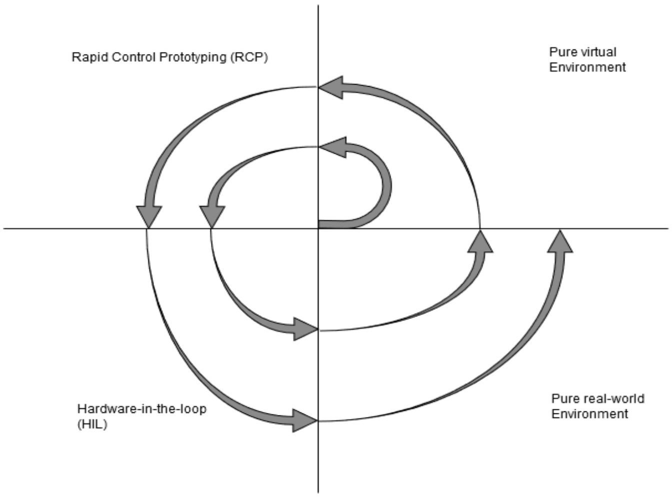

Figure 13 - XiL Approach

The RCP approach, regarding HIL technology, simulates the plant, including the physical presence of a real controller. HIL permits repetition and variation of tests on the actual or prototyped hardware without any risk for people or system. Tests can be performed under realistic and reproducible conditions, programmed and automatically executed [93]. The HIL tests can be integrated with some algorithms like HEMS [94] that offer the possibility to implement an optimization model which determines the optimal operational schedules considering consequently important effects. The major challenge is to create accurate and straightforward models [95].
The environment can be simulated, and this configuration brings many benefits, including repeatability and flexibility [96]. The EIL approach requests to project the entire simulation system. The high-speed real-time controller manages models implemented. A highly responsive dynamometer loads the connected engine as a real vehicle would, and the simulated vehicle speed trace follows the targeted driving cycle. Also, the vehicle pedal influences acceleration and speed. In this case, the control includes advanced techniques integrated into the whole vehicle. Vehicle parameters, including driveline configurations, are easily modified, and the effect on engine and vehicle performance can be analysed. In this context, the calibration step is relevant in the virtualization process and to configure the testbench [97]. Another exciting application of EiL is during the development of a new engine in that the over-all number of prototype vehicles are reduced in the early stage of the project. Based on that, the application of XIL methodologies on the test benches has multiple possibilities [98]. The intelligent combination and selection of vehicle calibration task have some benefits and limits in terms of management, hardware, software, compliance and testing.
The significant costs on vehicle testing are real road tests, the sluggish manufacturing of prototype production, a long-cycle test, and the dangerous test process. In this case, the simulation models of the characteristics of the vehicle and driver's behaviours are essential to the knowledge to check control performance and for evaluation of real-time embedded system before implementation on the real process. Therefore, this HIL test method, as a low-cost and short-cycle option, is a critical solution. The main applications are car following, cut in, cut out and hard brake. To achieve a system as close to reality, the real-time control development must be chosen precisely and with specific attention to the used hardware. The timing loop mechanism changes the performance in a hard way [99].

The steps followed in this approach are [100]:

1. Definition and built model;
2. Calibration of the model with errors (input, model and parameters);
3. Testing of functionalities using the HIL Platform and based on the real conditions (know extreme operating conditions and limitations, repeatable reliable, possible to have a connected device in a communication system with an integrated control system or emulating power source);
4. Replace the virtual device or sensor with a real one.

The XIL test like shown is the best solution to reduce costs and include all technologies of the system considered to test controllers that will be integrated into the real system. The simulation accuracy is a significant result that is used for validating the model [101,102]. In the end, XiL represents an significant potential for cost reduction, especially for calibration and in global development.

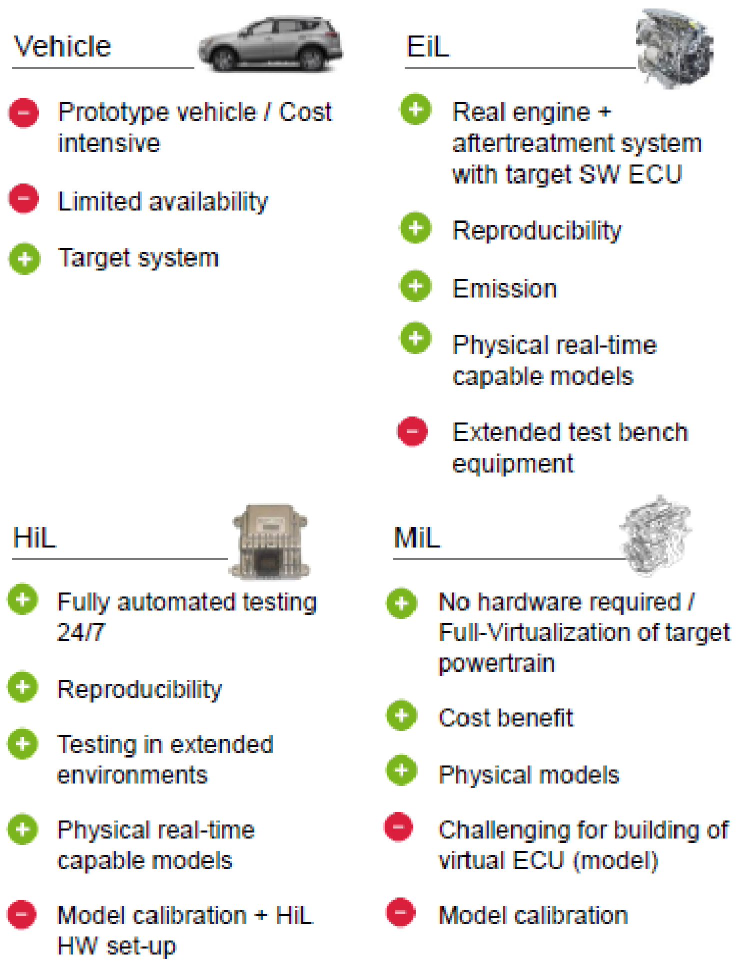

Figure 14 - Advantage and disadvantage of XiL phases

2.3. Fuel economy and driving cycles

The energy demand of a vehicle is determined under defined test conditions. Since this is an established method in which a predetermined test cycle is driven on a test bench, the results are not easily transferred to real life conditions. The respective actual energy demand, the fuel consumption and carbon dioxide emissions in vehicles with ICE are depending on driving style, track, road and traffic conditions, environmental influences, vehicle condition and equipment during actual driving. To determine the energy consumption, in various countries or international communities such as the EU, different test cycles are used. In vehicles with an internal combustion engine, a liquid or gaseous fuel is most common. Depending on the application, the energy requirement is given as litres of fuel consumed per 100 km of travel, or as fuel consumption in litres per hour. There are two approaches to determine fuel consumption. Either it can be calculated or it is determined by measurements.

The calculation of fuel consumption is commonly based on an engine map. In addition to the engine's power and torque characteristics, this provides further important data for the layout of the combination of internal combustion engine and torque response speed converter. The specific fuel consumption indicates the mass of fuel consumed per amount of energy released at the crankshaft, given in g/kWh. The fuel consumption of the vehicle also depends on the selected gear ratio between the engine and the drive axle. By choosing a different gear ratio, the operating point of the engine can be varied along the line of constant power. Thus, by shifting into an higher gear, the engine speed can be reduced, and the torque can be increased without changing the power output of the engine. As a result, the operating point is shifted into a more efficient area in the fuel consumption map (in the direction of the minimum specific fuel consumption).

The driver of the motor vehicle is responsible for controlling the driving speed and the driving direction. The emission may differ significantly from the standard consumption. The driver controller to govern the route include:

- The route selection: based on some criteria such as distance or time, a route, from all possibilities, is selected.
- Definition of desired track: within the selected route, the desired path must be defined monitoring the track information during driving.

- Following the desired track: the vehicle has to navigate on the track defined by its control elements.

The vehicle is driven based on these three tasks shown in figure 16. and represent the controlled system. The interactions between driver actions and vehicle response is considered as closed control loop.
The driving cycles are evolved and upgraded based on government and legislation of every country [103]. The studied methodologies are not limited to the choice of driving cycles capable of making consumption real but also include to monitor energy consumption. The pollutants, carbon dioxide, volatile organic compounds, nitrogen oxides and particulate are the results of the combustion of fuel and are regulated by countries directives. Emissions depend on different parameters and for this reason is classified based on vehicles types: cars, vans, buses, trucks and motorcycles.
The driving cycles are described throughout some features shown in Table 2. The three most important are distance, duration (time) and average speed.

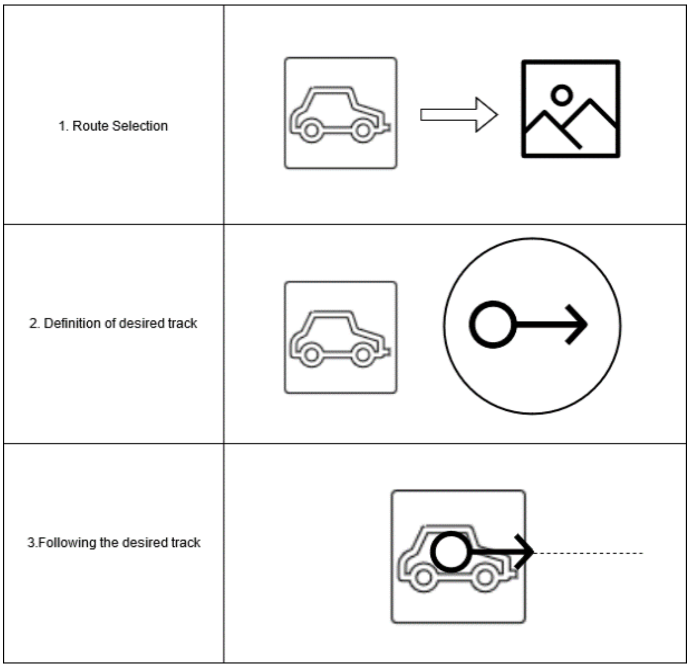

Figure 15 - Driving cycle controller tasks

Table 2 - Driving Cycle features

Feature	Detail
Distance	Total distance
Time	Total time Driving Time Acceleration Time Braking Time
Speed	Average Driving Speed Minimum Speed Maximum Speed
Acceleration	Average Driving Acceleration Minimum Acceleration Maximum Acceleration
Stops	Number of Stops Average Stop duration

The driving cycle used recently are:

- UDC or ECE-15: The Urban Driving Cycles represent a typical driving condition in Europe in a busy city with traffic and with a maximum speed of 50 km/h.
- EUDC: The Extra-Urban Driving Cycle is the high-speed road in the European cities with a maximum speed of 120 km/h;
- NEDC: The NEDC is composed of five main parts. Four-time of the ECE-15repeating without interruption followed by once EUDC. The first part represents the city condition, and low vehicle speed and low engine load define this type of cycle. The EUDC has more aggressive high vehicle speed. NEDC is used as a reference cycle for homologating vehicles until Euro 6 norm in Europe and some other countries.
- FTP-72: is the Federal Test Procedure used in the US to simulate an urban road with multiple stops.

- FTP-75: Federal Test Procedure derived from FTP-72 is a city driving cycle with are a series of tests defined by the US Environmental Protection Agency (EPA).
- HWFET: The Highway, fuel economy test, is used to assess fuel economy over highway driving cycle.
- US06: is a complement to what is missing in FTP-75 cycle. Indeed, this cycle has an higher top speed of 80 mph (130 km/h) and some higher acceleration which represents a much more aggressive driving behaviour.
- SC03: is a driving cycle particular in that is performed at 35°C ambient temperature. This is a request for taking into account the air-conditioning in fuel consumption and emissions calculations.
- JP 10-15 Mode: the official fuel-economy test cycle for new cars in Japan to simulate representative urban and highway driving patterns;
- JC08: chassis dynamometer test cycle in Japan introduced in 2011 and include different segments and speed variations to reproduce a congested traffic city;
- ARTEMIS-Urban, Rural, Motorway: are chassis dynamometer system procedure used in Europe with driving patterns derived from the analysis of a database containing real data.
- Worldwide Harmonized Light Vehicles Test Procedure (WLTP) is a global standard driving cycle since 2015 for determining level of pollutants and carbon dioxide emissions, fuel consumption, energy demand and electric range for vehicles based on real-driving emission data (RDE) and laboratory test. The RDE test measures the NOx and pollutants emitted by cars while driven on the road. Three different cycles are developed based on the power of the vehicle:
    - Class 1 – low power vehicles with PWr <= 22;
    - Class 2 – vehicles with 22 < PWr <= 34;
    - Class 3 – high-power vehicles with PWr > 34;

These driving cycles are significant for new cars in that allow to test and know emission and pollutants. R&R tests presented in the previous section assure that the results reflect real-world emission. The Paris Agreement is an agreement within the United Nations Framework Convention on Climate Change (UNFCCC), dealing with greenhouse-gas-emissions mitigation, adaptation, and finance, signed in 2016. From 2021, phased in from 2020, the EU fleet-wide average emission target for new cars will be 95 g CO2/km. This emission level corresponds to fuel consumption of around 4.1 l/100 km of petrol or 3.6 l/100 km of diesel. The fuel consumption value determines the emissions. The driving profile, in addition to the configurations and simulation setup, defines the behaviour of each component. The total consumption C_{tot} is calculated:

$$C_{tot} = \left(\frac{F_{tot}}{dist}\right) \cdot 2392 \qquad (2)$$

Where: is the total fuel consumed, is the distance in km, 2392 is the common value to calculate the grams of CO2 based on the chemical structure.

Table 3 - Driving Cycles

Characteristics	Unit	ECE 15	EUDC	NEDC
Distance	km	0.9941	6.9549	10.9313
Total time	s	195	400	1180
Average speed	km/h	18.35	62.59	33.35
Maximum speed	km/h	50	120	120
Maximum acceleration	m/s2	1.042	0.833	1.042

Characteristics	Unit	ADR 81/02	SFTP US06	SFTP SC03
Distance	km	19.44	12.8	5.8
Total time	s	1797	596	596
Average speed	km/h	38.95	77.89225	34.76183
Maximum speed	km/h	120	129.2303	88.19205
Maximum acceleration	m/s2	3.61	3.7833333	2.279904

Characteristic Artemis	Urban	Art Road	Motorway 130	Motorway 150
Duration (s)	993	1082	1068	1068
Distance (km)	4.874	17.275	28.737	29.547
Average speed (trip), km/h	17.7	57.5	96.9	99.6
Maximum speed, km/h	57.3	111.1	131.4	150.4

Characteristics WLTP	Unit	Class 1	Class 2	Class 3
Distance	km	8.091	14.664	23.262
Total time	s	1022	1477	1800
Average speed	km/h	28.5	35.7	46.5

Chapter 3. Case studies

In this chapter are presented the two case studies analysed, developed and implemented regarding different conditions. The former is an analysis of a linear model of MHEV with some control techniques applied and the integration of a GPS sensor. The latter is a non-linear model of a testbench with advanced control techniques involved testing different driving cycles. For both case studies, the performances are investigated related to the fuel economy and the emission, as published in [12,103,104].

3.1. Case study: Vehicle

In the vehicle case study, a Mild Hybrid Electric Vehicle is modelled, implemented and simulated. To guarantee good performances, the fundamentals steps follows are:

1. The model of the vehicle includes the full dynamics maintaining the linearity of the system and having the typical disturbance, the noise [1,12].
2. The control strategy is fulfilled based on the complexity of the linear system. The accuracy versus the fast response, obtained with the implementation of diverse controllers are compared, and the system is validated controlling the emission [103,104].

Besides, an integration with a GPS sensor is accomplished to investigate the behaviour of the entire system on real track to extend the results achieved on standard driving cycles.

3.1.1. Vehicle Model

The vehicle modelled is an MHEV. The standard coordinate system is defined with the origin located to the vehicle centre of gravity. The X-axis is aligned horizontally forward in the direction of travel. Perpendicular to the Y-axis points left in the direction of travel. The Z-axis points vertically upwards. The direction of rotation around the axes counter clockwise is defined as positive.

The rotational movements around the axes are referred to as roll, pitch and yaw. The model is derived from physical laws and supported to [105-107]. Different driving resistance forces preclude the movement of a motor vehicle. The sum of these resistances results in a demanding force required for the movement of the vehicle that must be overcome by the traction force applied by the drive train of the car. Thus, force equilibrium between the demand force and the traction force prevails for each state of motion. The traction force F_{Trac} is expressed as the sum of the drive torques of all driven wheels M_{ω} divided by the dynamic tire radius r_{dyn}:

$$F_{Trac} = \frac{\sum M_{\omega}}{r_{dyn}} \quad (3)$$

For movements, the motion equation resulting from forces and torque:

$$m_{\omega} \cdot \ddot{x} = F_{x_{\omega}} - F_{x_N} \quad (4)$$

$$m_{\omega} \cdot \ddot{z} = F_{z_{\omega}} - F_{z_N} - m_{\omega} \cdot g \quad (5)$$

$$\Theta_{\omega} \cdot \ddot{\varphi} = M_{\omega} - F_{x_{\omega}} \cdot r_{dyn} - F_{z_{\omega}} \cdot e_{\omega} \quad (6)$$

The wheel resistance is increased by the different road surfaces, pressure, deformation, friction and compression. Regarding that, the total force considers the sum of individual resistance of the wheel:

$$F_{\omega} = f_{\omega} \cdot m \cdot g \quad (7)$$

$$m = m_{F_{vehicle}} + m_{load} \quad (8)$$

The wheel resistance coefficient is determined by:

$$f_{\omega} = C_0 + C_1 \cdot v + C_2 \cdot v^4 \quad (9)$$

where the coefficient C_0, C_1 and C_2 are determined in coast-down tests.
The air drags resistance force F_{ADR} is influenced by the air drag coefficient:

$$F_{ADR} = c_W \cdot A \cdot \frac{\rho_{AD}}{2} \cdot v_{tot} \quad (10)$$

$$v_{tot} = v_{\omega ind} + v_{vs} \quad (11)$$

$$\rho_{ADR} = \frac{p}{R_{ADR} \cdot T} \qquad (12)$$

The cases that influence the vehicle are the downhill and uphill slope. On the slope the distribution of the weight of the vehicle change and the centre of gravity is split in parallel and perpendicular forces. Also, the vehicle model includes the acceleration resistance in case of unsteady state and the driving resistance in the steady-state. During the acceleration, the speed change dynamically, and the inertia must overcome this resistance [108-110]. The acceleration resistance formula can be expressed as:

$$F_{acc} = \left(m + \frac{\Theta_r}{r_{dyn}^2}\right) \cdot a_x \qquad (13)$$

Choosing the gear ratio, the equation is simplified as:

$$F_{acc} = \left(e_i \cdot m_{F_{vehicle}} + m_{load}\right) \cdot a_x \quad (14)$$

The air resistance can be calculated as:

$$F_{airRes} = c_w \cdot A \cdot \frac{\rho_{airdens} \cdot {v_{rel}}^2}{2} \qquad (15)$$

$$F_{Roll} = f_{Roll} \cdot \left(m_{F_{vehicle}} + m_{load}\right) \cdot g \cdot cos(\alpha) \qquad (16)$$

$$F_{grad} = \left(m_{F_{vehicle}} + m_{load}\right) \cdot g \sin(\alpha) \qquad (17)$$

$$F_{acc} = \left(e_i \cdot m_{F_{vehicle}} + m_{load}\right) \cdot a_x \qquad (18)$$

As presented, the vehicle longitudinal model implemented is composed of full dynamics including tire, inertia, vehicle body, road and wind [111-114]. The vehicle model is suitable for obtaining a view of the fundamentals principles of driving dynamics and provides useful results regarding trend predictions of individual vehicle parameters. The motion depends on the traction force. This force, in opposition to the total driving resistance, is calculated as:

$$F_{driv\_res} = f_{Roll} \cdot m \cdot g \cdot cos\,\alpha + c_w \cdot A \cdot \frac{\rho_L}{2} {v_{rel}}^2 + m \cdot g \cdot sin\,\alpha +$$

$$+ \left(e_i \cdot m_{F_{vehicle}} + m_{load}\right) \cdot a_x \qquad (19)$$

$$F_{driv\_res} = F_{airRes} + F_{Roll} + F_{grad} + F_{acc} \quad (20)$$

$$P_{drive} = F_{driv\_res} \; \cdot \; v5 \; (F_{airRes} + F_{Roll} + F_{grad} + F_{acc}) \cdot \; v \; (21)$$

According to the simplification implemented, the traction forces related to the acceleration and climbing performance highly correlated to the position of the centre of gravity of the vehicle.

The lateral vehicle dynamics include Newton's equation of motion:

$$m_{F_{vehicle}} \cdot a_y = F_{sf} + F_{sr} \qquad (22)$$

The moment's equilibrium in the z-axis:

$$\theta \cdot \ddot{\psi} = F_{sf} \cdot I_f - F_{sr} \cdot I_r \qquad (23)$$

The force of inertia acting in the vehicle's centre of gravity, correlated to the centrifugal force resulting from the road curvature:

$$m_{F_{vehicle}} \cdot a_y = m_{F_{vehicle}} \cdot \frac{v^2}{r} = m_{F_{vehicle}} \cdot v\left(\dot{\psi} - \dot{\beta}\right) \qquad (24)$$

For the tyre forces:

$$F_{sf} = c_{sf} \cdot \alpha_f \qquad (25)$$

$$F_{sr} = c_{sr} \cdot \alpha_r \qquad (26)$$

The vehicles differ from the set of parameters c_w, A and m.

The formulas can be interpreted using the symbols:

$*_{ADR}$ is the reference for the Air Drag Resistance;
A is the projected face in [m²];
a_x is the longitudinal acceleration of the vehicle [m/s²];
a_y is the lateral acceleration of the vehicle [m/s²];
c_W dependent on the shape of the vehicle drag coefficient;
e_i is the mass factor (>1), which considers the moments of inertia of the accelerated, rotating masses in the drive train;
e_ω is the eccentricity value;
F is the Force;
F_{airRes} is the air resistance;
$F_{driv_{res}}$ is the total driving resistance;
F_{grad} is the slope resistance [N];
F_{Roll} is the rolling resistance in [N];
f_{Roll} is the rolling resistance coefficient;
F_{Trac} is the traction force;
F_{x_N} is the transmitted vehicle force from the wheel hub to the axle in x-direction;
F_{x_ω} is the circumferential force in a wheel;
F_{z_N} is the transmitted vehicle force from the wheel hub to the axle in z-direction;
F_{z_ω} is the wheel force including rolling and slip resistance;
g = 9,81 m / s² the gravitational acceleration;
I is the inertia;
M_ω is the total mass of driven wheel;
$m_{F_{vehicle}}$ is the mass of the vehicle in [kg];

m_{load} is the mass of the load of the vehicle in [kg];
m_ω is the mass of a wheel;
P_{drive} is the drive power;
p is for air pressure;
R_{ADR} gas constant of air;
r is the curve radius;
r_{dyn} is the dynamic tire radius;

s is for the side;
T is for the temperature;
v is the driving speed;
${v_{rel}}^2$ is the relative speed of vehicle $[m/s]^2$;
$v_{\omega ind}$ is speed of the wind;
v_{vs} is the vector sum of vehicle speed;
ω is the wheel;
$\ddot{x}$ is the acceleration of the wheel in x-direction;
$\ddot{z}$ is the acceleration of the wheel in z-direction;

α is the angle in radiant;
α_f and α_r are the tyre slip angle front and rear;
$\dot{\beta}$ is the side slip angle speed;
Θ_r is the reduced moment of the inertia;
Θ_ω is the wheel moment of inertia including brakes;
θ is the pitch angle;
$\ddot{\varphi}$ is the rotational acceleration;
ρ_{ADR} is the air drag resistance density;
$\rho_{airdens}$ is the air resistance density at the level sea (20° C) kg/m3;
$\dot{\psi}$ is the yaw velocity;
$\ddot{\psi}$ is the yaw acceleration;

3.1.2. GPS Sensor integration

Recent trends in automotive industries to reach highly accurate position information and improve safety have led to introduce the global positioning systems (GPS). The GPS technology allows for tracking and managing car position with an error that not grow with the time. The track describes a motion of the vehicle in the Euclidean space as a sequence of geo-referenced with a specific frequency. The other benefits deriving to the GPS are the high accuracy position estimation and the continuous availability of the satellites. However, the application of GPS demands tracks [115-117].

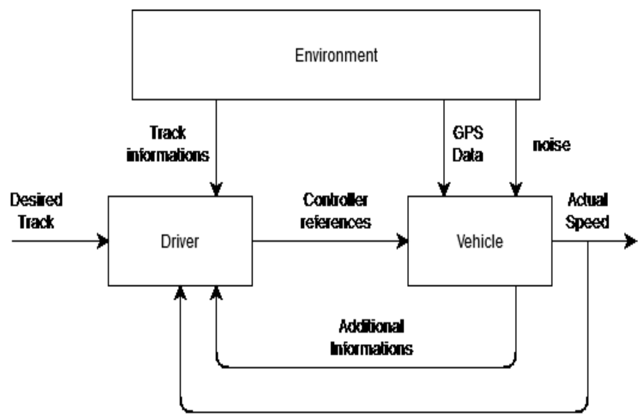

Figure 16 - GPS sensor integration schema

The road features [104] can be summarized in:

1. Exclude short cycle: is evaluated the length of the overall track and the values are compared with the speed values.

2. Organize the direction of trajectory data: the values define a specific route in an exact direction. For R&R acquisition test, the track is repeated following the same direction.

3. Smooth the speed: the systematic error can be quickly deleting and, using long cycles, are reduced.

4. Divide a trip into several segments: based on the results during the long cycles the operating conditions, in case of real-world acquisition, is emerged that smaller segments can better describe the working conditions. This is possible considering the demand to exclude short cycle.

5. Exclude traffic influence: another technique useful in case of intensive traffic jam is to exclude some route to have a more realistic tests; at the other hand the traffic jam can be used as evaluable measures in case of the metropolitan city urban roads.

6. Repeat the same route: Useful for the R&R tests and to validate the measures.

The GPS sensor can be considered as an alternative approach regarding extend the results of this thesis in case of vehicle's simulation. The integration of this sensor in the vehicles permits to test different driving cycle and various operating conditions. In addition, the model is enhanced with real data, and the emission values reflect the environment [118,119].

The GPS-recording vehicle trajectory P, with R data points, is mathematically defined in the simulator as:

$$P_R = [(p_1, t_1), (p_2, t_2), \dots, (p_R, t_R)] \qquad (27)$$

where P represents a trajectory and p represents a data point on the trajectory with three variables: latitude, longitude and altitude; R is the total number of the data points of trajectory P. Each data point of the trajectory is recorded at timestamp t. The GPS recording interval remains the same for all trajectories (1 second). Therefore, the timestamp feature is excluded from the dataset for computing reduction. A simplified data point is expressed by the following:

$$p_R = [(lat_1, long_1, alt_1), \dots, (lat_R, long_R, alt_R)] \quad (28)$$

Supposing vehicle at the same altitude during the simulation, the Euclidian distance from p_R is calculated with the following formula where the time from one data point to the next is 1 second:

$$dist(p_t, p_{t+1}) = \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2} \quad (29)$$

Where x_r is the rth latitude and y_r is the rth longitude.

The GPS measures originate to a sensor located in a car with a manual shift and cruise control. The cruise control is an essential feature to maintain a constant speed for a selected time. The GPS sensor is acquired every one second in the string format: [Timestamp, speed, altitude, latitude, longitude].

The altitude is correcting with EGM96 (Earth Gravitational Model), a geopotential model of the Earth's surface computed from a spherical harmonic representation through degree 360. For this case study, the timing and speed are used to verify the correspondence between the measured value with the car’s speed value and evaluate the timing performance. The tests are conducted in areas with good GPS reception quality, and this has assured to provide the required signal accuracy. GPS data give an excellent instantaneous measurement of vehicle speed. The simulations of this use case are shown in section 3.1.4. PID Control and Fuzzy Supervisor.

3.1.3. Fuel Consumption on driving test cycles

The driving performance of a motor vehicle is characterized by the maximum speed as well as by the maximum acceleration and climbing ability. These can be determined from the comparison of the maximum available power of the vehicle and the required power of the driving condition [120,121]. The comparison is made using the tractive force (from the Eq. (3)), which can be expressed as the sum of all driving torques of the wheels or the hub torque M_N divided by the dynamic tire radius:

$$F_{Trac} = \frac{\sum M_{\omega}}{r_{dyn}} = \frac{M_N}{r_{dyn}} \qquad (30)$$

For calculation of the fuel consumption for a driving cycle, the unsteady driving conditions must also be considered in addition to the phases of the constant travel. The speed profile is therefore divided into small time intervals. The corresponding acceleration can be assumed to be constant. The speed at these intervals is averaged. At this point, the fuel mass consumed during a small-time interval can be calculated. In the simulations, the fuel consumption is calculated by the equation (2) as presented in paragraph 2.3 Fuel economy and driving cycles. In any case, it is difficult to measure "absolute" fuel savings, which are enabled by a 48-volt hybridization. For instance, a 48-volt mild hybrid vehicle with a BSG configuration, which shows a 13% better fuel economy during the NEDC, may save up to 21% during real-world urban driving. At the same time, the same car may only deliver a one-digit percentage of fuel-saving on the motorway. In other words, the fuel economy of a vehicle is strongly influenced by the driving situation and especially by the number of so-called load changes. The term load-change denotes any situation during which the driver requests either more or less torque at the pedal. It is therefore not strange that the driving style is another significant influence on fuel efficiency. All percentage figures given for a 48-volt hybrid car need to be seen in the context of the cycle or trip and the type of driver. A cooperative driver, who does not override hybrid operating strategies but makes optimal use of them, will save more fuel than a sporty driver. For this reason, the GPS sensor implemented strongly enhance the results obtained.

3.1.4. PID Control and Fuzzy Supervisor

The proposed control system is composed of a PID controller supervised by a fuzzy controller. The choice of using this supervisor controller derives from the process of literature review. The PID control is limited when the disturbs and noise are added to the vehicle's model. The Fuzzy management is proposed for the EVs applied to different components for the balance of battery charge, for the energy management and the optimization of the systems [103, 122-125]. The fuzzy set theory, optimizing the system, decreasing the emissions, and the results proved that this technique provides better solutions for MHEVs. The steps of the fuzzy supervisor are:

- Fuzzification: the data in the input is split into some parts; these are compared with the range defined by the conditions of the membership function.
- Rules: the rules are defined in the membership function and include
- Inference: this mechanism computes the intermediate output, namely PID parameters range.
- Defuzzification: The resulted output is converted to a parameter for the controller.

Finally, the fuzzy supervisor will tune the PI parameters automatically. The controller is a PI, without the derivative component.

The Fuzzy supervisor is designed with one input and two outputs. The input signal considers the error speed, the difference of reference speed demand request by the driver and the vehicle speed. The result of this "fuzzy" difference is the error. The goal of the controller is to control the error speed in such a way that the desired vehicle speed is achieved. The vehicle speed has white noise added that represents the real driving conditions, and in the simulation, the GPS define the tracks to follow. To implement the controller, a behaviour analysis concerning the input outlines three range for the error parameters. The different shapes possible for the membership function are triangular, trapezoidal, bell-shaped. The sensitivity, computational efficiency, output proprieties, values and domain depend from this shape. For the supervisor, a triangular shape is considered, as shown in Fig. 17.

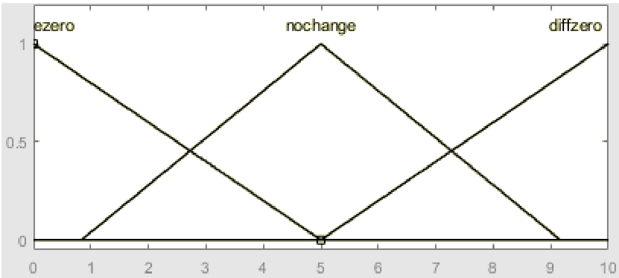

Figure 16 - Fuzzy shape

The three range is:

- Ezero: in this case, the error is limited or negative;
- Diffzero: if the vehicle speed is not nearby to the reference and it is over the limit;
- Nochange: if there is no change from the value range from time t to time t+1.

In the second step, the rules are defined. The rules in a fuzzy PI controller are IF-THEN type. A fuzzy rule can be written as:

$$If\ x_1\ is\ A_1\ then\ y_1\ is\ B_1\ and\ y_2\ is\ B_2 \qquad (31)$$

Finally, the outputs are chosen and represent the proportional and integral parameters for the PI controller. These outputs are defuzzificated for tuning the PI control. The controller for track reference has been implemented in Matlab/Simulink considering full electric vehicle model.

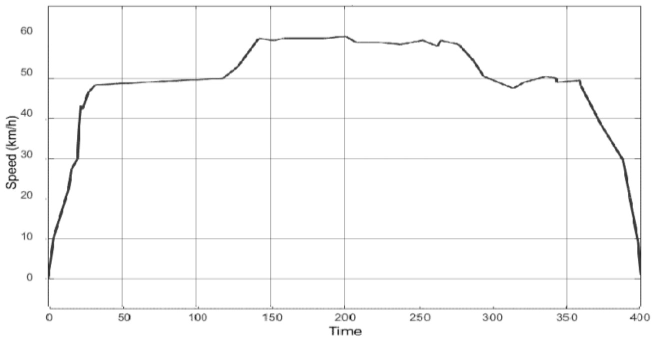

Figure 17 - Desired Urban track

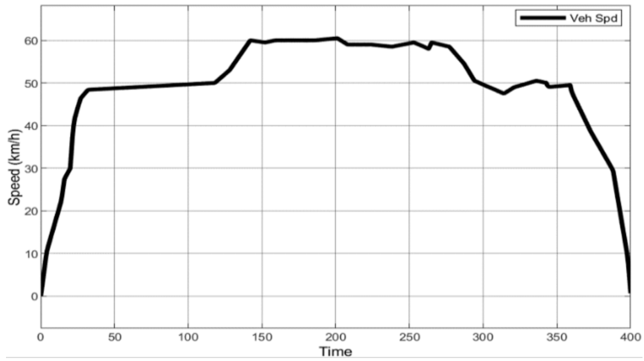

Figure 18 - Vehicle urban track with fuzzy supervisor

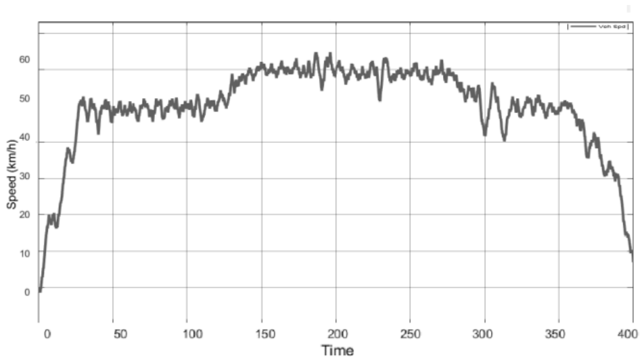

Figure 19 Track with conventional PI

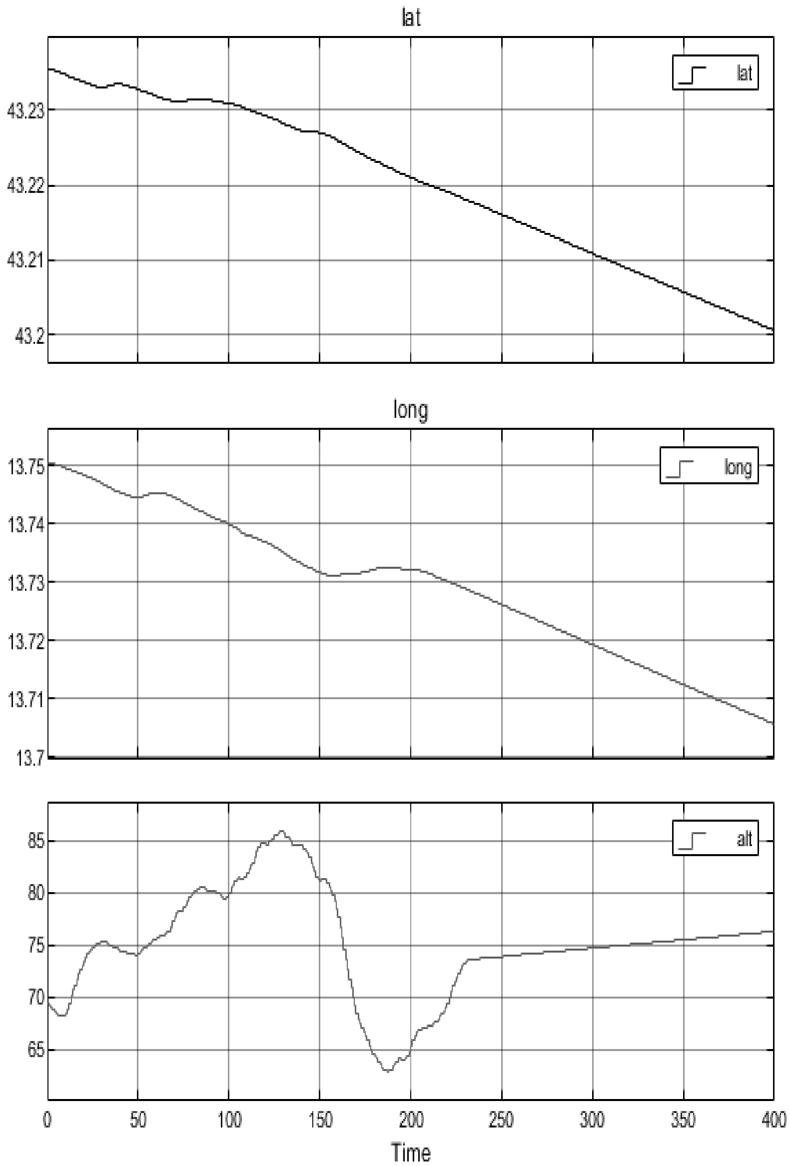

Figure 20 - GPS latitude, longitude and altitude urban track

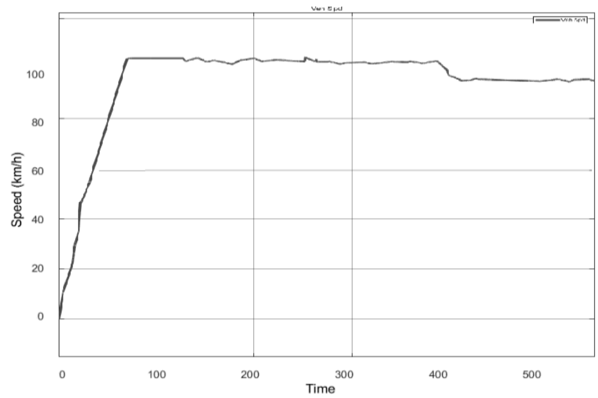

Figure 21 - Desired extra-urban track

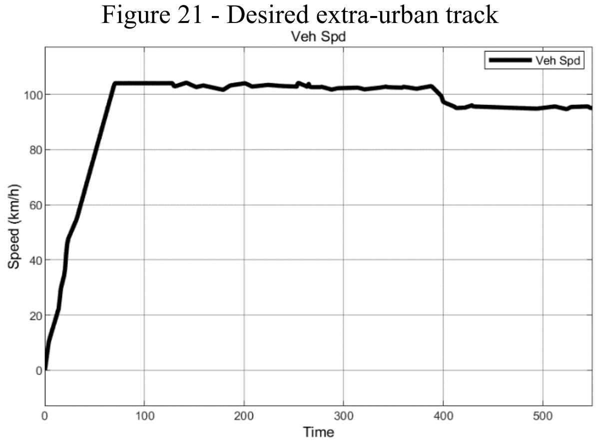

Figure 22 - Vehicle extra-urban track with fuzzy supervisor

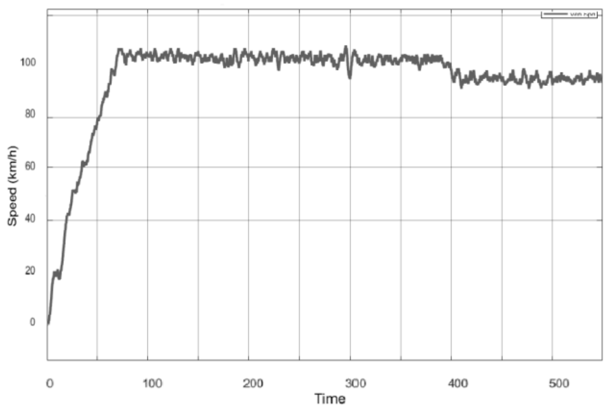

Figure 23 - Vehicle urban track with conventional PI

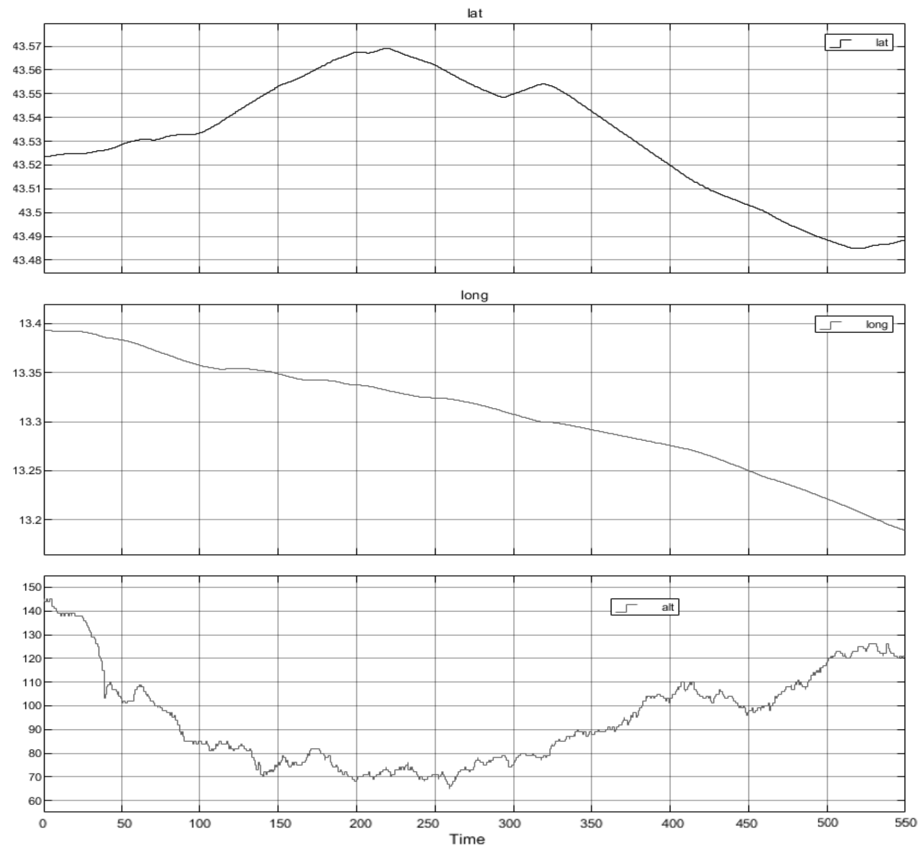

Figure 24 - GPS latitude, longitude and altitude extra-urban track

The vehicle model, in this case study, is controlled by varying the pedal of the vehicle instantly. The speed of the overall vehicle is compared with reference speed from GPS data calculated on the desired track selected.

The driving cycles are summary in Table 4.

Table 4 - Driving Cycle summary emission with fuzzy supervisor

Fuel Consumption		
Cycle type	***Distance (m)***	***CO_2 (gr/km)***
Urban Cycle	5324.7	70.46
Extra-Urban Cycle	14470.5	62.45

The track considered are chosen based on the knowingly real-world environment and on the presence of a noise that affects the vehicle speed during the route. The urban track has the speed varying in the range 47-61 km/h, and the extra-urban track range is 95-105 km/h. The time for the former is 400 seconds and for the latter is 550 seconds. The fuzzy supervisor and the PI controller act on the error speed to follow the track maintaining low fuel economy. The error stored creates a delay that provides output in terms of speed error, and it is limited, so the results can be successfully handled. GPS data is shown in figure 21 for the urban track and figure 25 for the extra-urban track.

In vehicles with an internal combustion engine is expected that the energy requirement and, consequently, the consumption is given as litres per 100 km of travel or as litres consumed per hour. There are two approaches used to determine fuel consumption and to define the emission of CO2.

The former is the calculation of the fuel consumption of a known engine. This fuel consumption calculated is based on the engine map. In the engine map, the specific fuel consumed is related to the energy from the crankshaft and the adequate engine power. The fuel consumption is affected by the operating point of the gear ratio chosen. The operating point causes the shifting in a specific working area in the fuel map and thus, define the fuel consumption. The latter include the measure of the fuel consumption carried out on a roller testbench. This approach is used in section 3.

The role of the fuel consumption measure is vital in modern vehicles and is relevant to define the car's production in the automotive industries. For this reason, the calculation of CO_2 is essential. Based on the fuel consumption measured in the two circuits chosen the CO_2 emissions are shown in Table 5.

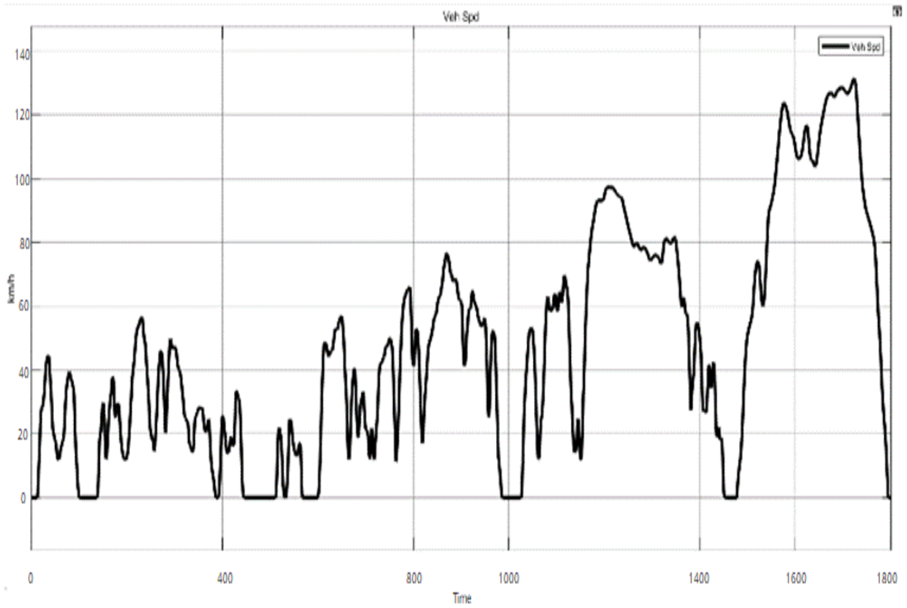

Figure 25 - WLTP driving cycle

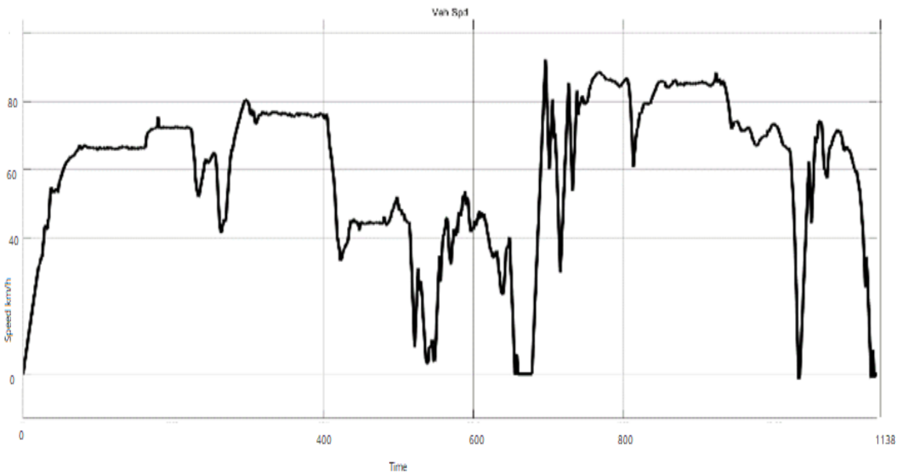

Figure 26 - CUA driving cycle

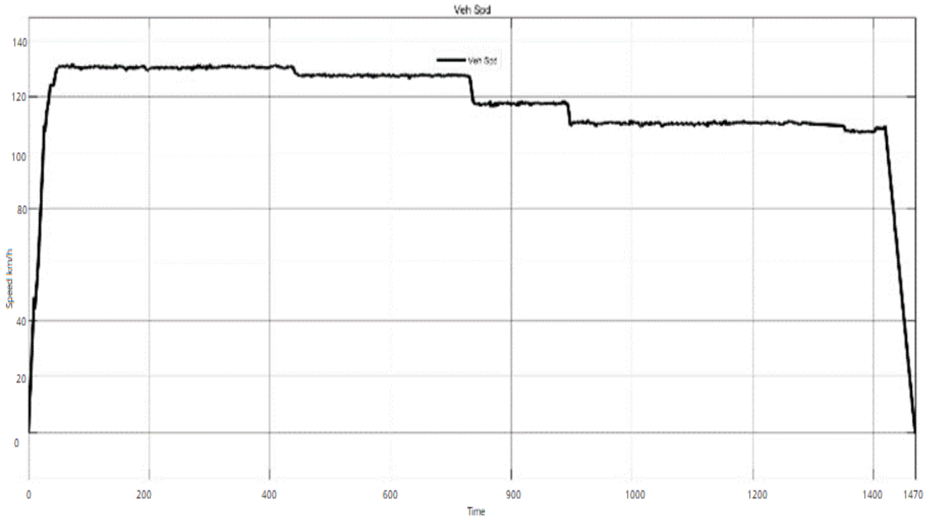

Figure 27 - CEA driving cycle

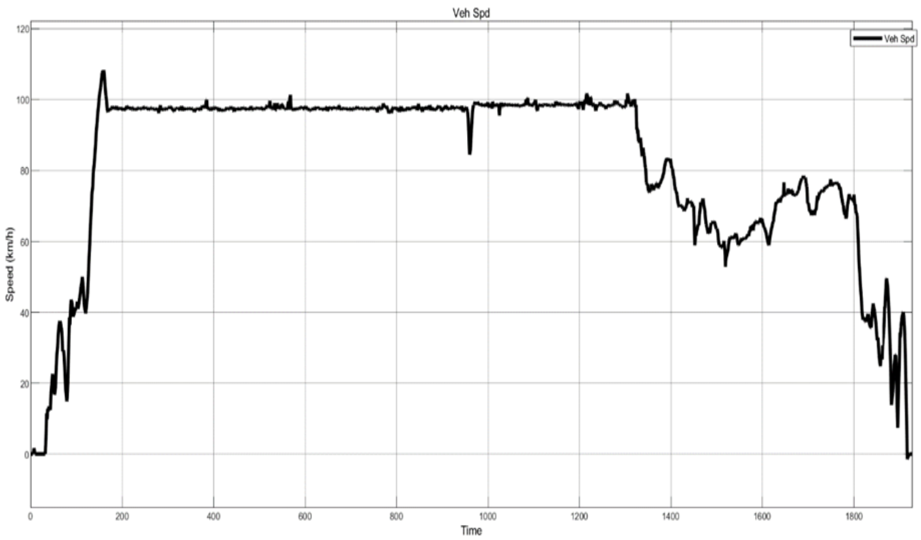

Figure 28 - CUEA driving cycle

Table 5 - Driving cycle emission detail with fuzzy supervisor, GPS track

Cycle	Emission gr CO_2/km	Distance (m)	Standard Deviation
WLTP	50.95	23266	36.03
CUA[a]	62.93	18820	22.03
CEA[b]	27.62	47800	18.69
CUEA[c]	46.23	43750	25.08

3.1.5. Model Predictive Controller

To improve the system, the control strategy is upgraded, including a new control on the virtual vehicle. The Model Predictive Controller (MPC) is implemented in the EM control unit [12]. The MPC is designed in dimensionless form as follows:

$$x_p(k+1) = A_p x_p(k) + BS_i u_p(k) \qquad (32)$$

$$y_p(k) = S_0^{-1} C x_P(k) + S_0^{-1} DS_i u_p(k) \qquad (33)$$

where A_p, B, C and D are the constant state-space matrices; $S_i$is a diagonal matrix of input scale factors; S_0 is a diagonal matrix of output; x_p is the state vector; u_p is the vector of plant input variables; y_p is the vector of plant output variables.

The resulting plant model has the following equivalent form:

$$x_p(k+1) = A_p x_p(k) + B_{pu} u(k) + B_{pv} v(k) + B_{pd}\,\mathrm{d}(k) \quad (34)$$

$$y_p(k) = C_p x_p(k) + D_{pu} u(k) + D_{pv} v(k) + D_{pd}\,\mathrm{d}(k) \quad (35)$$

where $C_p = S_0^{-1}C$, B_{pu}, B_{pv} and B_{pd} are the columns of BS_i. D_{pu}, D_{pv} and D_{pd} are the columns of $S_0^{-1}DS_i$. $u(k)$ is the manipulated variables, $v(k)$ is the measure disturbances and $\mathrm{d}(k)$ is the unmeasured input disturbances.

The model of the motor describes the behaviour. The MPC is based on this model and offers some benefits as easy to control, implement, understand and addition of constraints in cost function [126-129]. In this case the control implemented is a combination of direct torque control and model predictive control that have led to the implementation of Predictive Torque Control.

Table 6 - Driving cycles details tested with MPC

Characteristics	Unit	ECE 15	EUDC	NEDC
Distance	km	0.9941	6.9549	10.9313
Total time	s	195	400	1180
Idle (standing) time	s	57	39	267
Average speed (incl. stops)	km/h	18.35	62.59	33.35
Average driving speed (excl. stops)	km/h	25.93	69.36	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

NEDC: Four repetitions of ECE 15 followed by one EUDC

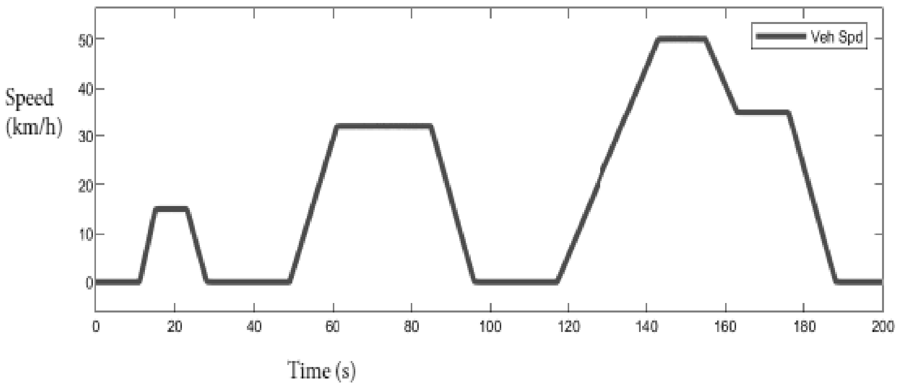

Figure 29 - ECE-15 Cycle with MPC

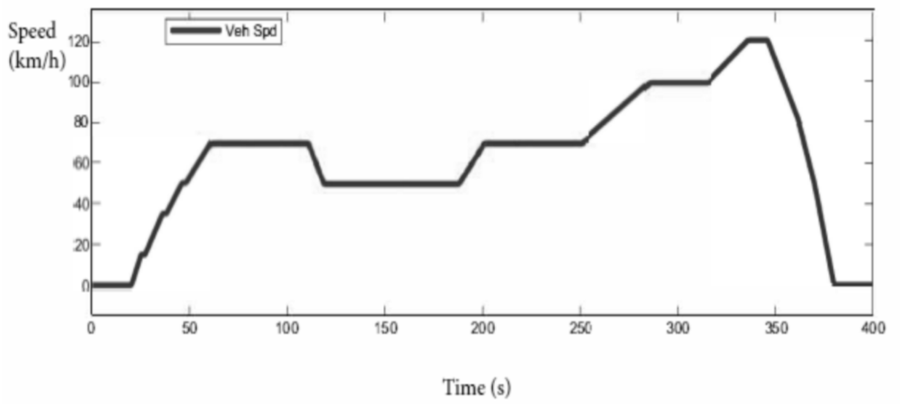

Figure 30 – EUDC Cycle with MPC

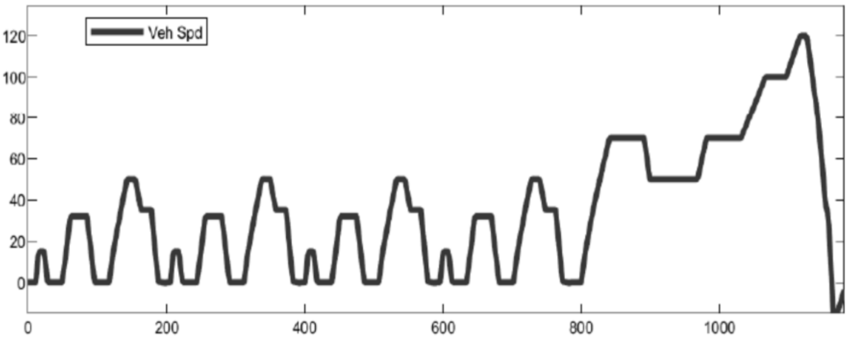

Figure 31 - NEDC Cycle with MPC

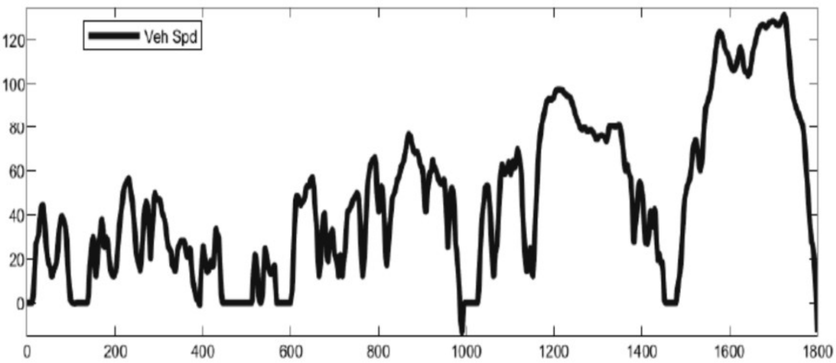

Figure 32 - WLTP Cycle with MPC

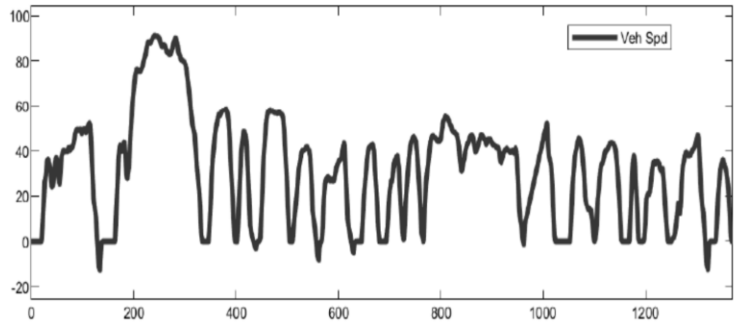

Figure 33 - UDDS Cycle with MPC

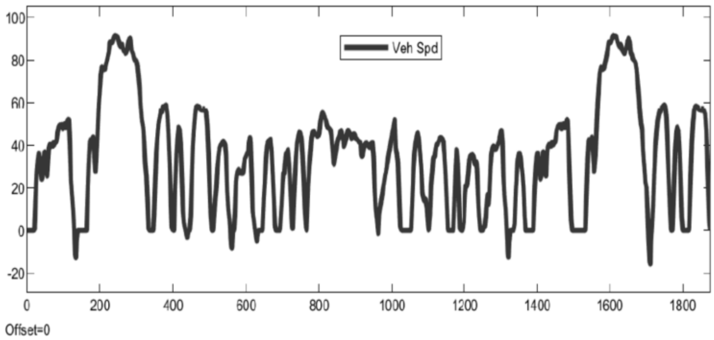

Figure 34 - FTP Cycle with MPC

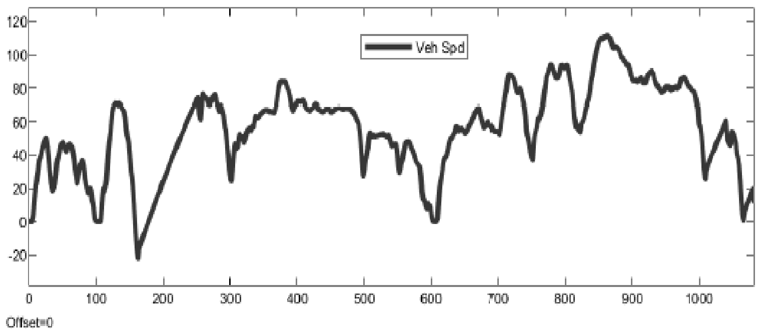

Figure 35- Artemis Road Cycle with MPC

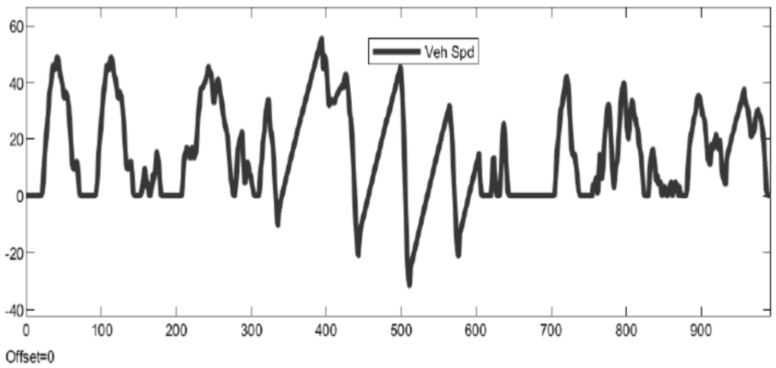

Figure 36 - Artemis Urban Cycle with MPC

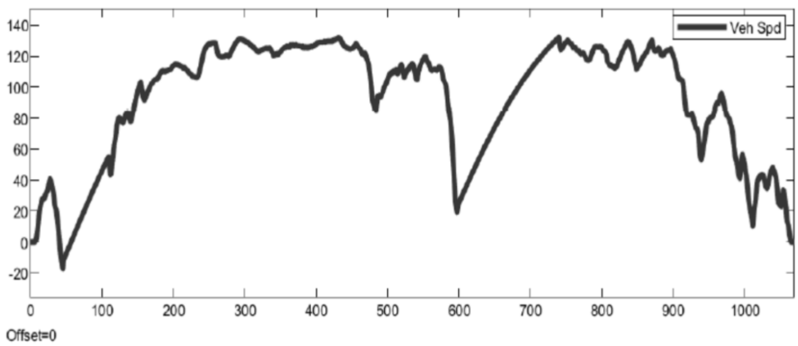

Figure 37 - Artemis Motorway 130 Cycle with MPC

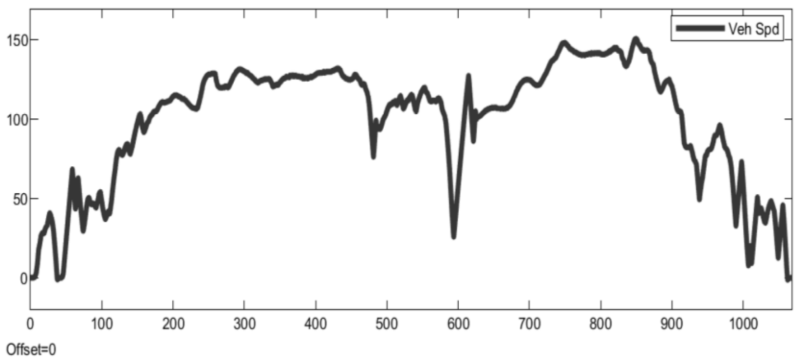

Figure 38 - Artemis Motorway 150 Cycle with MPC

Table 7 - Driving Cycle emission results with and without MPC

Driving Cycle	Consumption MPC (gr of CO2/km)	Consumption Without MPC (gr of CO2/km)
ECE 15	84,2122	115,8639
EUDC	35,4201	52,3552
NEDC	47,4958	68,9475
WLTP	38,7439	59,6351
US FTP-72 (UDDS)	53,4914	80,1326
Artemis road	32,5134	50,3686
Artemis Urban	102,8975	145,2176
Artemis rw130	17,7410	31,7304
Artemis rw150	16,0875	21,1085
FTP	51,5420	62,4333

Experimental results, confirm that the high speed of detection provided by this approach allows a satisfactory transition from pre-fault to the post-fault mode of operation even using these strategies. This section presents results using the MPC applied on the virtual MHEV model and tested on different driving test cycles: ECE15, EUDC, NEDC, WLTP, UDS, FTP and Artemis. In table 7 the fuel consumption is shown to demonstrate the performance of the system and to validate the controller applied on tests cycles. Without the MPC the noise on the model significantly increases the value of the emission and the simulations run request more computational time. It is clear that the emissions show the various values changing based on the different conditions and driving cycle. A graph including the limit of emissions is shown in [12] to compare the result with the Government restriction.

3.2. Case study: Testbench

In the testbench case study the focus is the overall system, and it is not limited to the modelling of an electric vehicle. The tests consider the environment and the functionality of the system. The model of the dynamometer is non-linear, and to improve performance, the linearization is requested. The system studied represents an advanced innovative testbench which includes the Engine-in-the-loop approach and advanced control techniques. The emission value obtained from the fuel consumption is the reference for the validation of the system, as published in [1,130,131].

3.2.1. Testbench Model and Engine-in-the-loop integration

The modelling of the testbench in detail is expensive and a non-linear model represents the induction machine. Also, the parametrization of the induction machine non-linearity is highly demanding for a typical automotive testbench commissioning process. The inverter integrated with the testbench has a fixed supervisor, and the structure is unknown. In this context, the dynamometer system could be modelled as a low-pass filter with fast dynamics [132,133]. The testbench structure includes a dynamometer connected to the DUT with a shaft: a general schema is shown in figure 40, for detail, see Section 2.1 Testbench. The connected device changes the initial conditions on the calibration step.

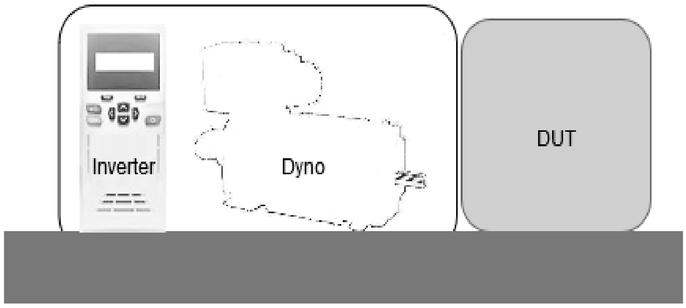

Figure 39 - General test bench schema

A simplified non-linear mathematical model of a testbench for differential gears, including the unit under test could be designed following the methods presented in [133]. The plant also includes the model of inertia, and the two parts of the testbench are treated as two mass oscillators [132]. The considered model is:

$$\Delta\dot{\varphi} = \omega_{EM} - \omega_D \quad (36)$$

$$\theta_{EM}\dot{\omega}_{EM} = T_{EM} - c\Delta\varphi - d(\omega_{EM} - \omega_D) \quad (37)$$

$$\theta_D\dot{\omega}_D = c\Delta\varphi + d(\omega_{EM} - \omega_D) - T_D \quad (38)$$

where:
EM denote the Device Under Test that can be an Engine or a Motor;
D the dyno variables;
ω_x is the speed;
θ_x the inertia;
$\Delta\varphi$ the torsion of the shaft;
T_x the estimated or measured torque;
c is the stiff constant;
d is for damping.
A sweep test, with torque as a reference value for the inverter controller, is designed for the initial calibration process. The torque mode test consists of variable torque signals with different amplitude and frequency to find the best-fit time constants for the Dynamometer Machine System [133-135].

The calibration plays a crucial role in a testbench, and the parameters setting is often a fundamental step which influences the tests [136]. The calibration process is a signal that allows assessing the exact initial configuration. The computation is in real-time for the DSM. Parameters are initialized after a prior off-line estimation. Then, the torque signal starts with a fixed amplitude and increasing frequency, and it is evaluated the response. The previous calibration phase is repeated, increasing amplitude and testing the new value for every frequency. The online calculation provides time constant for the system. This dynamic calibration has been achieved considering the transfer function between reference torque and IM air gap torque and shaft speed. In a MIMO system, a controller with low overshoot is significant for improving dynamics compensation and consider the different steady-state. Considering that the reference for the inverter is a torque signal, the test is run in the torque mode. This dynamic calibration has been achieved considering the transfer function between reference torque and induction machine air gap torque and shaft speed. The dynamic compensation, for better control with less overshoot, in this MIMO system is needed when different steady-state models are included in the controller.

The introduced model is used to simulate the testbench with an approach: The Engine-in-the-loop method [137-139]. In addition, in this use case, the test benches are set with the parallel hybrid P2 configuration parameters designing a Mild Hybrid Electric Vehicle. The same setup can also be used for electric motor, considering that the initial tests for calibration are different. The P2 configuration allows to run in Hybrid Mode: in this instance, ICE and EM are used at the same time to increase the efficiency and reduce fuel consumption.

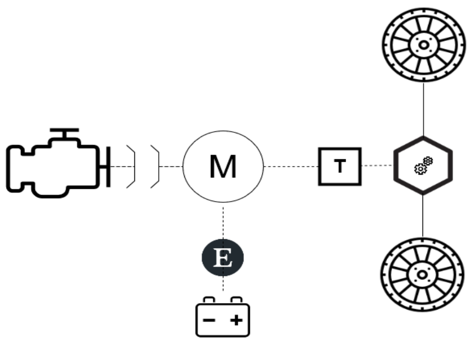

Figure 40 - P2 Configuration schema

To have an entire valid vehicle system, is designed an electric motor model in addition to the testbench model. The electric motor model includes a standard model with drive electronics in torque-control mode or current-control. The motor is limited in speed and torque. The output is a torque value assumed to track the torque reference demand with the time constant. The detailed model integrates a three-phase inverter with a vector controller. In the simulation, the three-phase machine has sinusoidal back electromotive force (back EMF) waveform. The rotor is salient-pole, and the stator windings are connected to an internal neutral point.

The battery used in the EiL-simulation includes three different scenarios. The first one uses a generic battery model where the effects and temperature is the nickel-metal-hybrid type. The second one is a battery model as a series of internal resistance plus a charge-dependent voltage source defined by:

$$V = \frac{V_{nom} \cdot SOC}{1 - \beta \cdot (1 - SOC)} \qquad (39)$$

where V_{nom} is the nominal voltage and SOC is the State of Charge. The third one is a battery model with ten cells. The cells include circuits for voltage, thermal model, SOC and power. As input for the battery, there is a DC-DC converter to convert the signal from the motor on the bus to request to the battery the right voltage and current.
The interaction of the vehicle model with the testbench assures a high-quality simulation and performs better results in terms of accuracy and precision, including the real-data environment.

3.2.2. Adaptive Model Predictive Controller

The entire non-linear testbench system presented in the previous section, requests a robust control approach. After the literature review, it is clear that the controller must optimize the interaction and improve the testbench in terms of dead time compensation, accuracy and performance. The hybrid simulation schema, designed and presented in the previous sections, is controlled by an Adaptive Model Predictive controller [140-144]. The adaptive control purposes to have a better control action and more robustness when the process is in transient. The proposed control method guarantees the robustness of the system and fast response to the changes in real-time.

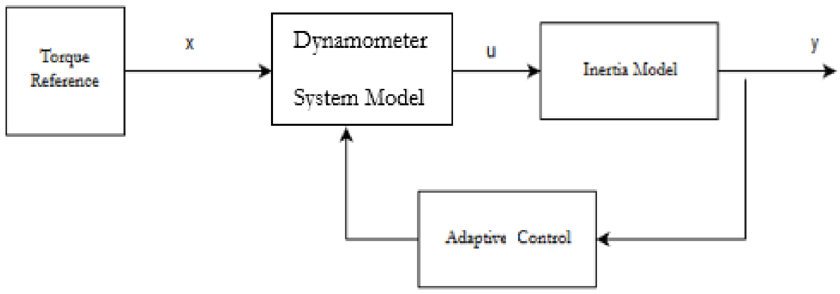

Figure 41 Implemented control schema

The Model Predictive Controller is a robust control that helps to solve the non-linear problem. The Kalman filter can be represented by:

$$x_{k+1} = Ax_k + Bu_k + w_k \qquad (40)$$

where x_{k+1} and x_k are the discrete-time instant system state variables at k+1 and k respectively. u_k is the control vector and A, B are the matrices that link the state variables at time k to k+1 and w is the weight at time k.
The Kalman Gain is K:

$$K = P_p H^T \left[H \cdot P_p \cdot H^T + R\right]^{-1} \quad (41)$$

The residues matrix to predict the error is r:

$$r = \Delta z - H \cdot X_P \quad (42)$$

In the end, the correction is obtained with:

$$X_c = X_p + (K^* r) \quad (43)$$
$$P_c = [I - K^* H] P_p \quad (44)$$

The equations for the online state estimation on Matlab are implemented as follows. The state prediction uses the matrices:

$$X(.|k) = \psi \cdot x(k) + y \cdot u(k-1) + \vartheta \cdot du(.|k) + (X_i) \quad (45)$$

(16) is optional extension for system, which are linearized in a stationary operating point.

Output prediction:

$$Y(.|k) = \gamma \cdot X(.|k) \quad (46)$$

Free response:

$$f(.|k) = \gamma \cdot \Psi \cdot x(k) + Y \cdot u(k-1) \quad (47)$$

Free control error:

$$e(.|k) = r(.|k) - f(.|k) \quad (48)$$

The process, in detail, follows the steps:

1. State update
2. Update variance of an error on the state
3. Gain matrix Kalman Filter
4. Update estimation state, the variance disturbs on the state and loop.

Adaptive MPC controllers adjust their prediction model at run time to compensate for nonlinear or time-varying plant characteristics.

The adaptive controller executes in parallel an on-line Kalman Filter (KF) state estimator combined with a Least Square Algorithm (LSA) for parameters estimation. This method is useful to estimate the value parameters. The LSA is based on the minimization of the square error between the estimated and measured output using the cost function $J(x)$:

$$Min\ J(x) = \left(Z - h(x)\right)^T W\left(Z - h(x)\right) \tag{49}$$

Based on the non-linear state estimation model, the objective function to minimize is:

$$J(x) = \sum \frac{\left(z_i - h_i(x)\right)^2}{\sigma_i^2} \tag{50}$$

This algorithm updates the covariance and estimated parameters on-line when the vehicle is running. The estimated value of the objective function is corrected for each time, and the parameters are estimated step by step until the satisfied values are gained. The parameter adaption updates guarantee to maintain the system performance. An evaluable parameter that helps to validate this controller is the economical fuel consumption improvement given by the AMPC compared to the most straightforward PID controller. The KF is used for the dead-time compensation of DSM. In the KF and the A(k) and B(k) matrix needs to be updated each step in the algorithm by the LS. The controller is also adapted by the online estimation of the parameter by the LS. The estimation of disturbance with dead-time compensation is important to correct the distortion and the non-linearity in the overall model. The undesirable deformation and significant suppression of oscillations are achieved using this approach. Thanks to the real data and including the calibration step in the process, the system reaches a good performance from the beginning and delete initial oscillations typical in this approach.

3.2.3. Fuel Consumption on driving test cycles

The fuel consumption measurements can be carried out on a roller test bench, a closed test track or public roads. The consumption measures on a roller test bench allows reproducible test conditions and shorter set-up times, as the measuring devices do not necessarily need to be mounted in the vehicle [145]. The methods used for consumption measurement differs for results obtained: consumption in a fixed time, volumetric offline measure and emission investigation. These are the measurement of the continuous flow rate or the quantity measurement about a specified time or distance.

The fuel consumption can be determined from the amount of fuel consumed at a specific time. In the case of a quasi-static volumetric measurement, the heat expansion of the fuel must be considered in the calculation of the fuel consumption. This includes the thermal expansion coefficient of the fuel car: the reference temperature and the fuel temperature.

With the gravimetric and the quasi-static volumetric measuring method, very accurate measured values can be obtained, but not real-time values for the consumption. For a closed-loop at the behaviour in different driving situations, for example in non-steady-state operation, only flow measurements with a dynamic-volumetric measurement method are used. However, due to the low flow rates in motor vehicles, the technical requirements are high for measuring devices such as turbines, pumps or heated thermocouples.

A third method determines the fuel quantity based on the carbon balance from the gas composition. This procedure is used in emission investigations in which the gas is collected and examined. This method is very accurate but involves a high effort.

In this thesis, the author chooses to use the second method and calculate the emission with the equation (2) in paragraph 2.3. Fuel economy and driving cycles. The results include the driving cycles plot respecting the physical constraints and the emission value (Table 10).

The control system has a direct influence on fuel consumption and driving performance. For this reason, are tested different driving cycles from governments and legislations of various countries. An important aspect is a central role of driving cycles in emission measurement [60].

In this case study, the significant contribution is the use of an AMPC and the inclusion of road noise to control the testbench. In the initially tracks a comparison with the AMPC and PID controller is shown to demonstrate the benefits of the advanced control strategy. Besides, this approach allows for repeatability and reproducibility tests (R&R tests).

Another significant benefit is the reduced time for setting the configuration and the possibility to virtualize components. In either approach, the fuel consumed can be measured or calculated, based on the information available.

The driving cycles are described throughout some features shown in Table 9.

The driving cycles tested are:

1. UDC or ECE-15: Fig. 43;
2. EUDC: Fig.44;
3. NEDC: Fig.49;
4. WLTP: Fig. 50;
5. FTP-72: Fig.51;
6. ARTEMIS Urban: Fig. 52;
7. ARTEMIS Rural: Fig.53;
8. ARTEMIS Motorway: Fig.54.

These driving cycles are significant for new cars in that allow to test and know emission and pollutants measurements. Besides, assure that the results reflect real-world emission.

The New European Urban Cycle (NEDC) has been chosen as the target testing cycle for the control comparison. To be more accurate, the NEDC is divided into the two parts that make it up. For that, in the first simulations, the UN/ECE Elementary Urban Cycle and the UN/ECE Extra-Urban Driving Cycle are shown separately to prove and evaluate the control performance and disturbance rejection. Excluding the disturbances on-vehicle, the results obtained to the control type is similar and is not required the complexity of the AMPC. At the other hand, introducing the disturbance on-vehicle, the performance decreases, and an advanced control strategy is necessary. For the simulations that follow the four comparison cases, shown in Table 8, the AMPC demonstrate to maintain the performance of the system. The AMPC was implemented on Simulink and Matlab code. The high-level control models are designed in Simulink. The ICE torque is determined by the gas pedal value. The driving profile is used for investigations the EiL test setup and in order to verify the proposed control strategy. Non-measurable quantities are estimated by filtering or calculated using the validated models.

The simulations of the cycles are extended to cover different situations and to validate the system in real scenarios. Every test scenario was chosen to include an extensive operation range to investigate the performance of AMPC. In Figure 43 and 33 is shown the difference from controllers. The AMPC controller results more robust, and the error is limited in the range 1,3 rpm to 2 rpm that is in the constraint of 3 rpm. The 3 rpm represents the minimum quantity evaluable when is used EiL approach, and it is defined as minimum speed that it is possible to measure on the physical system. The AMPC controls the reference rapidly to the single setpoints while satisfying the constraints.

Based on the Table, Figure 45 and 46 show the general information about cycle 1 and case 1 and 2; figure 47 and 48 show the vehicle information respectively about topic 3 and 4.

The other driving cycles are presented as a plot of the vehicle's speed in figure 49-54 as explained in the previous page. Furthermore, are shown the behaviour of electric motor modelled as motor or generator and the response of the engine, including the speed, the torque and the power in the case of advanced control techniques. The summary of the fuel consumption regarding AMPC controller is shown in Table 10.

Table 8 – Controller comparison driving cycles

	Control Type	Vehicle Type	Road
Case 1	PID	1	The UN/ECE Elementary Urban Cycle 1
Case 2	AMPC	1	The UN/ECE Elementary Urban Cycle 1
Case 3	PID	1	UN/ECE Extra-Urban Driving Cycle 2
Case 4	AMPC	1	UN/ECE Extra-Urban Driving Cycle 2

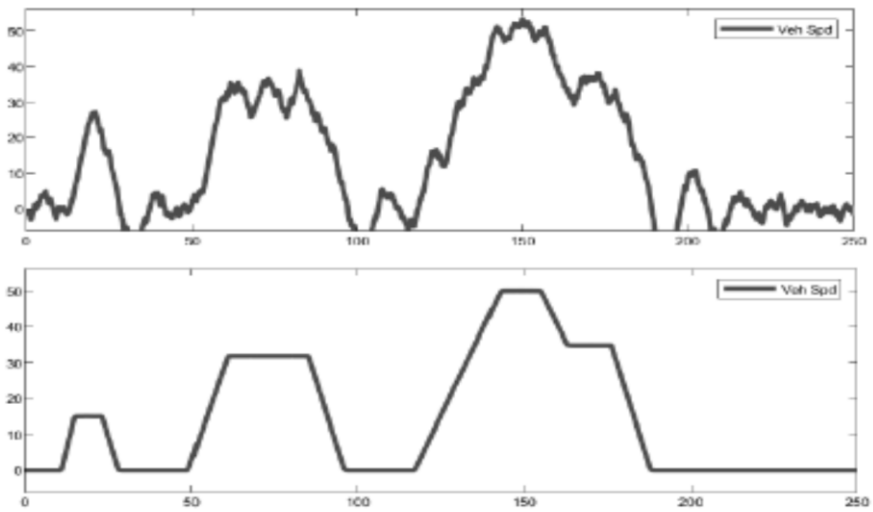

Figure 42 - Cycle 1 PID (top) and AMPC (down) comparison

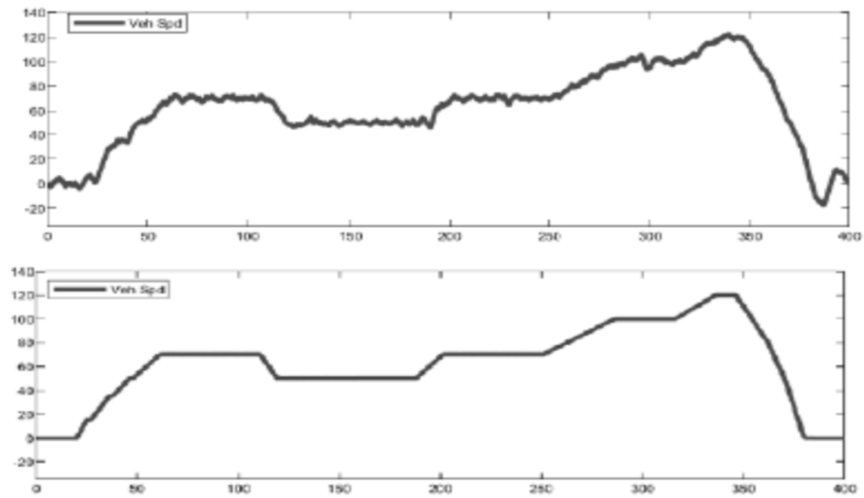

Figure 43 - Cycle 2 PID (top) and AMPC (down) comparison

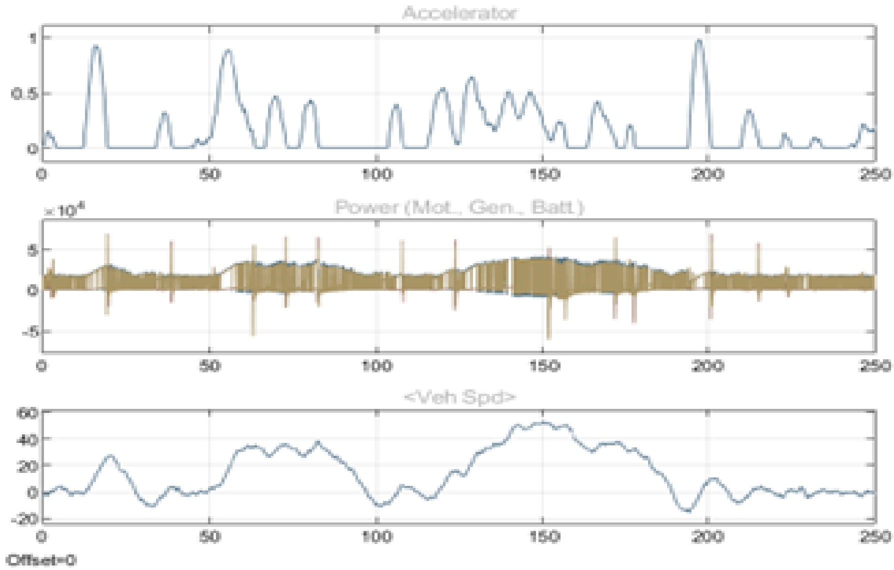

Figure 44 - PID controller Cycle 1 general info

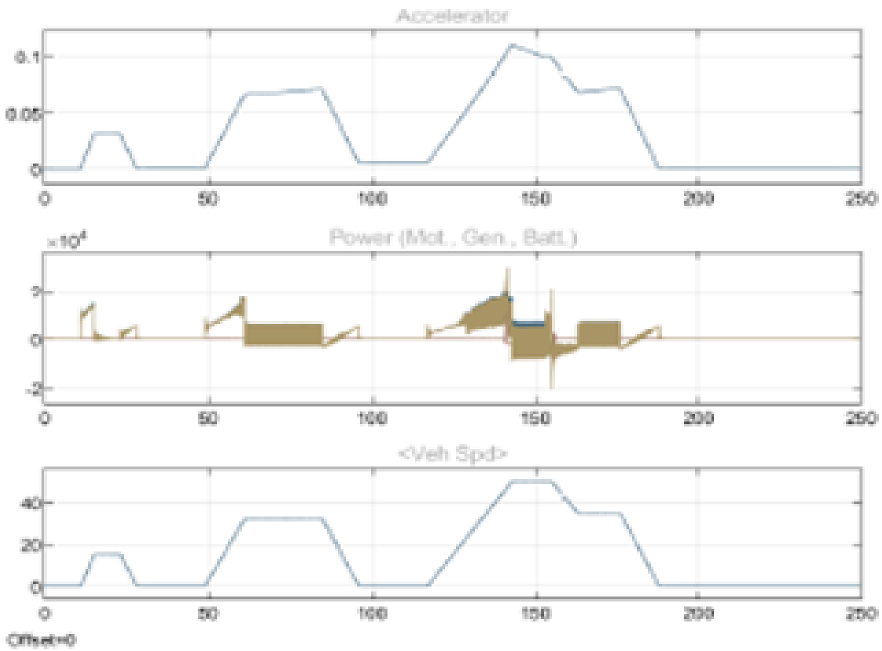

Figure 45 - AMPC controller Cycle 1 general info

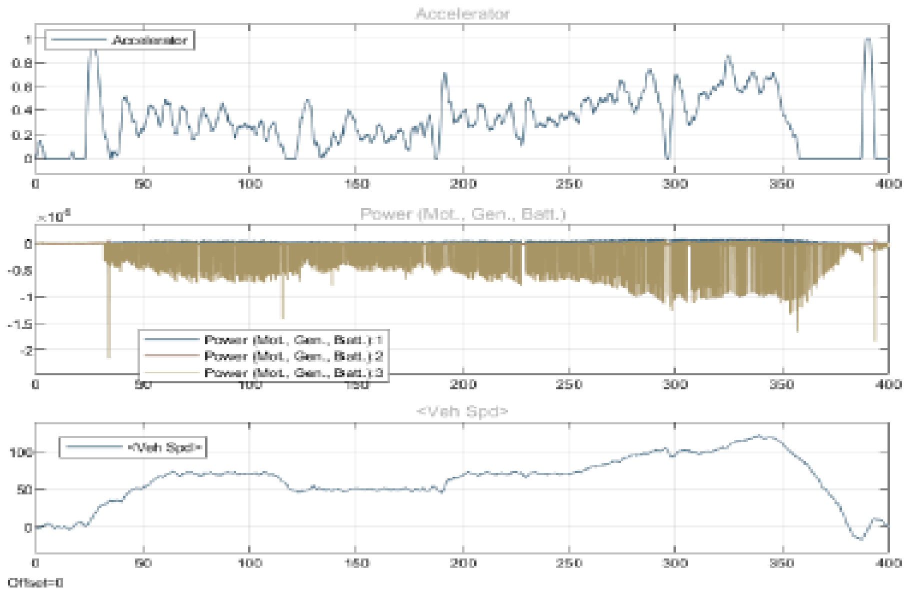

Figure 46 – PID controller Cycle 2 general info

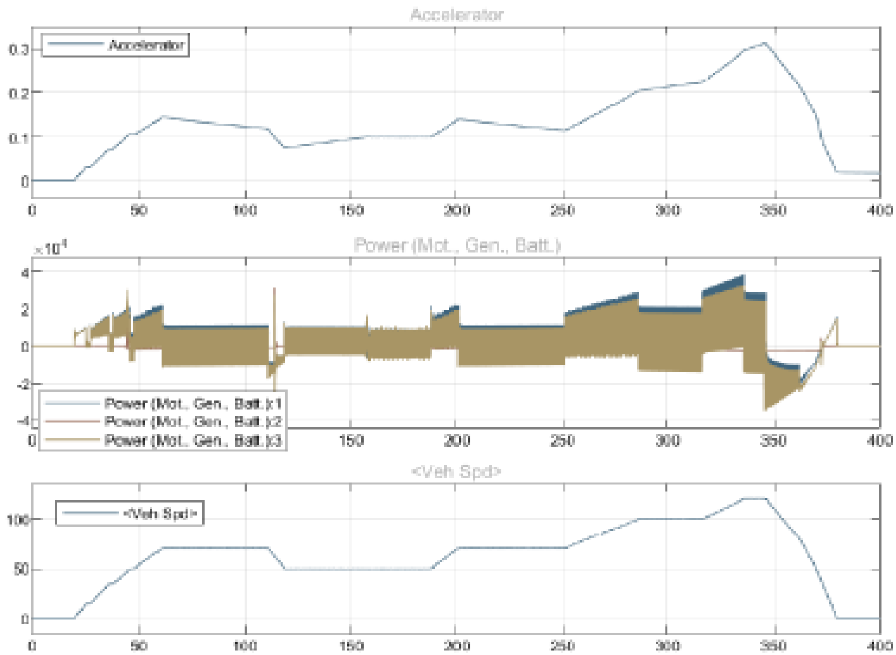

Figure 47 - AMPC controller Cycle 2 general info

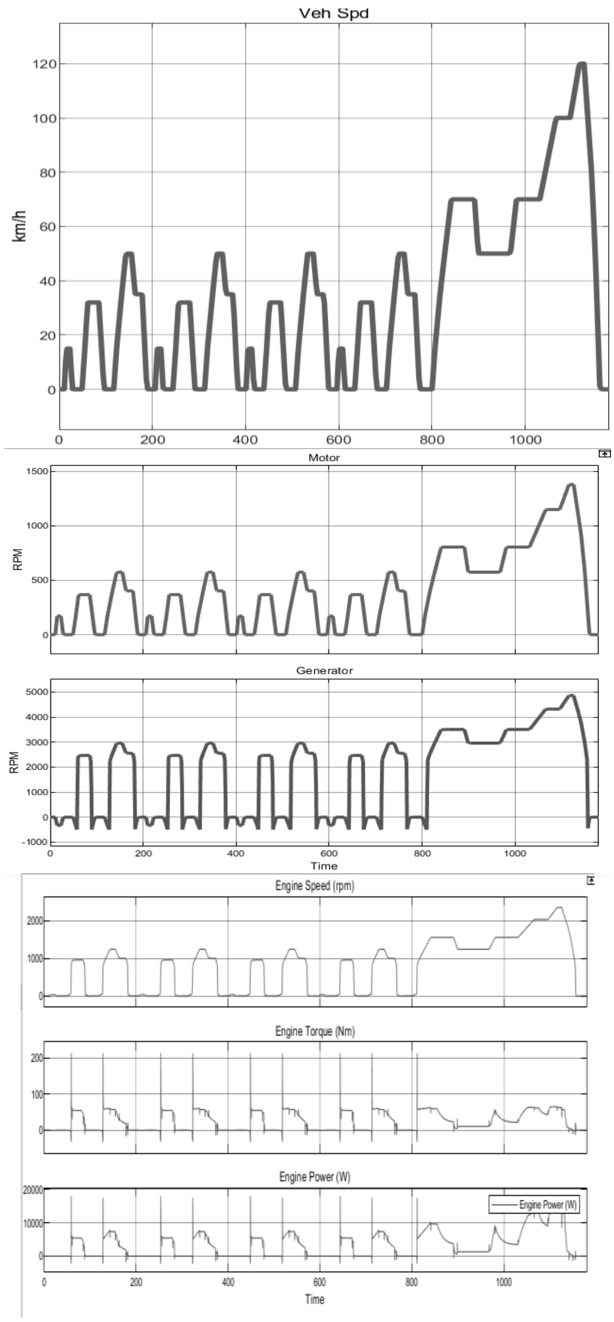

Figure 48 - NEDC on virtual test bench with AMPC

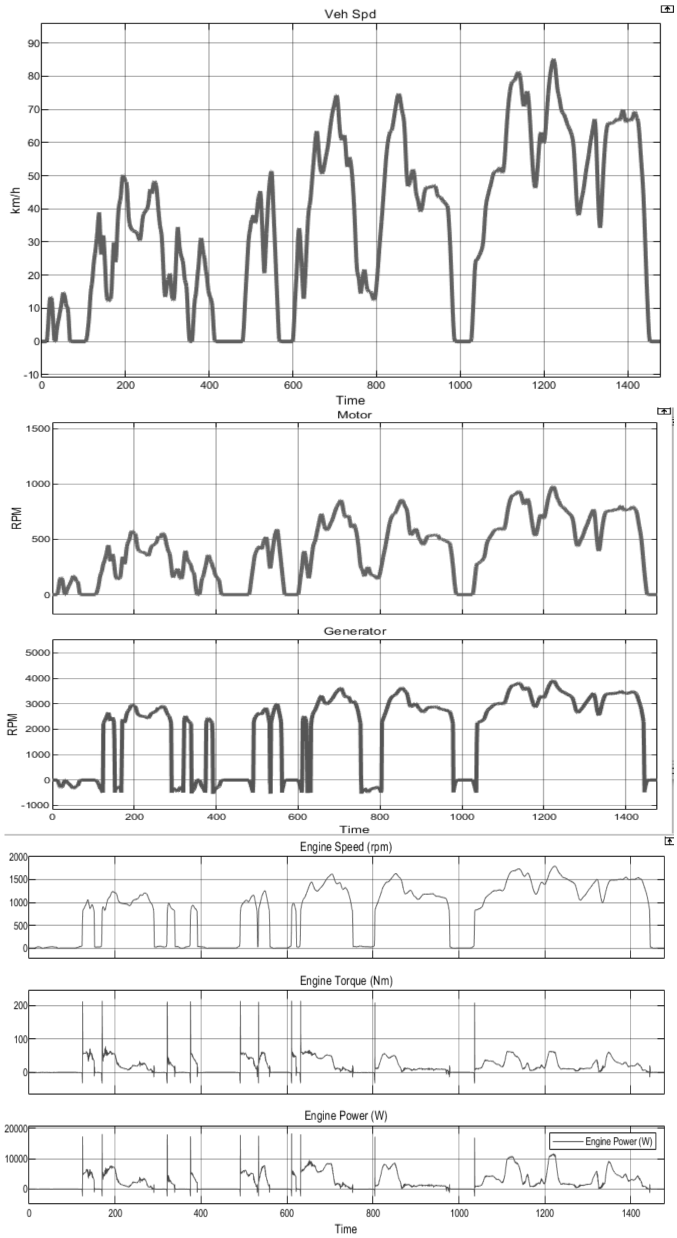

Figure 49 - WLTP cycle on virtual test bench with AMPC

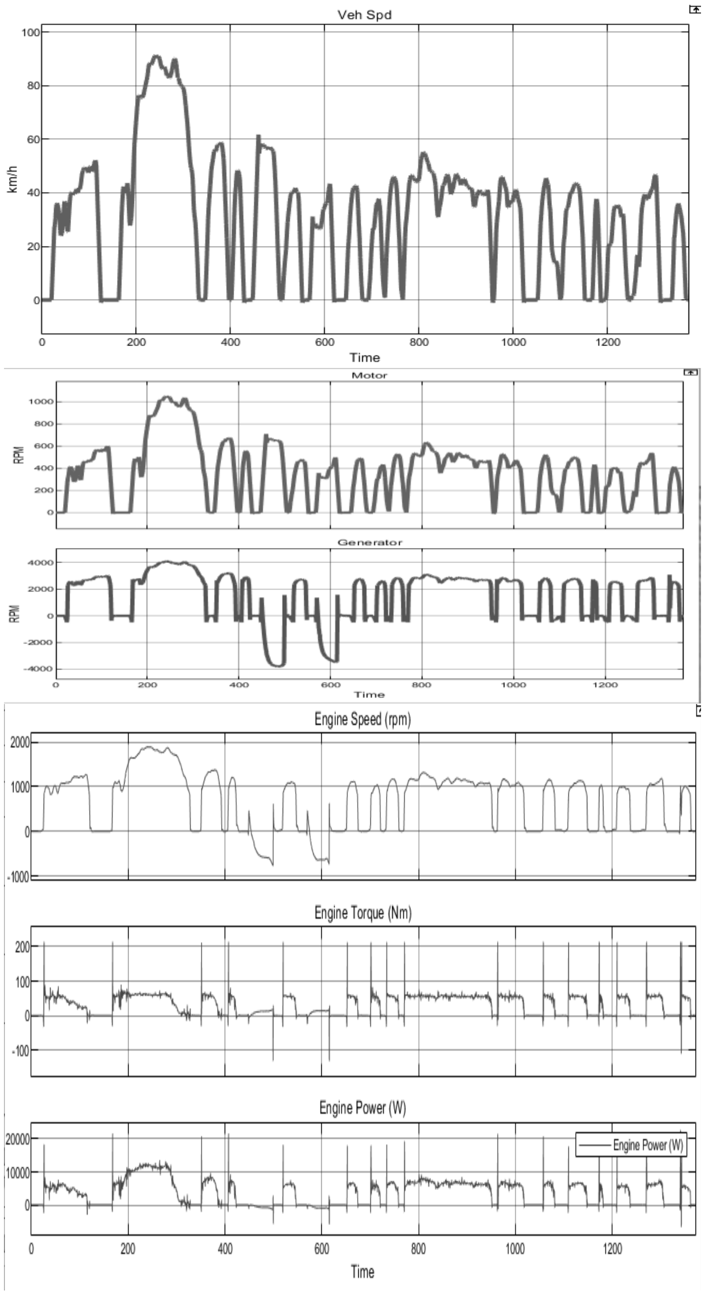

Figure 50 - FTP-72 cycle on virtual test bench with AMPC

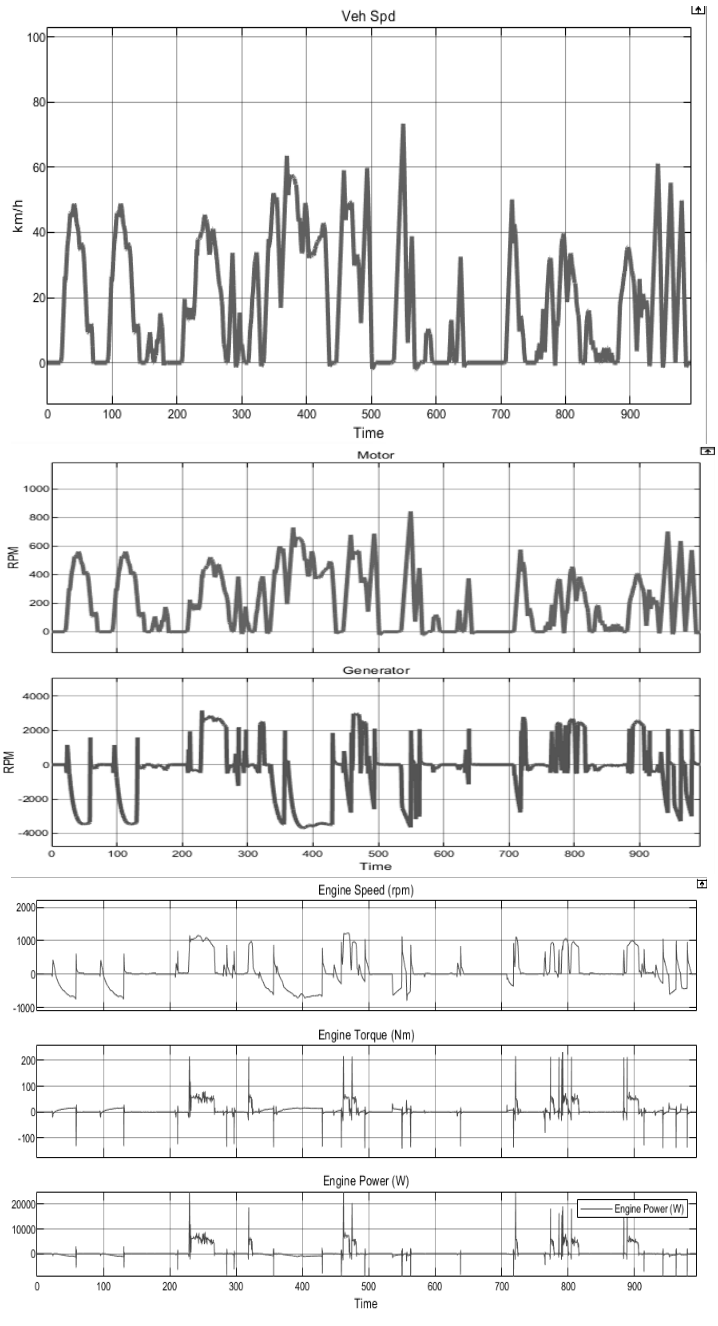

Figure 51 - ARTEMIS Urban on virtual test bench with AMPC

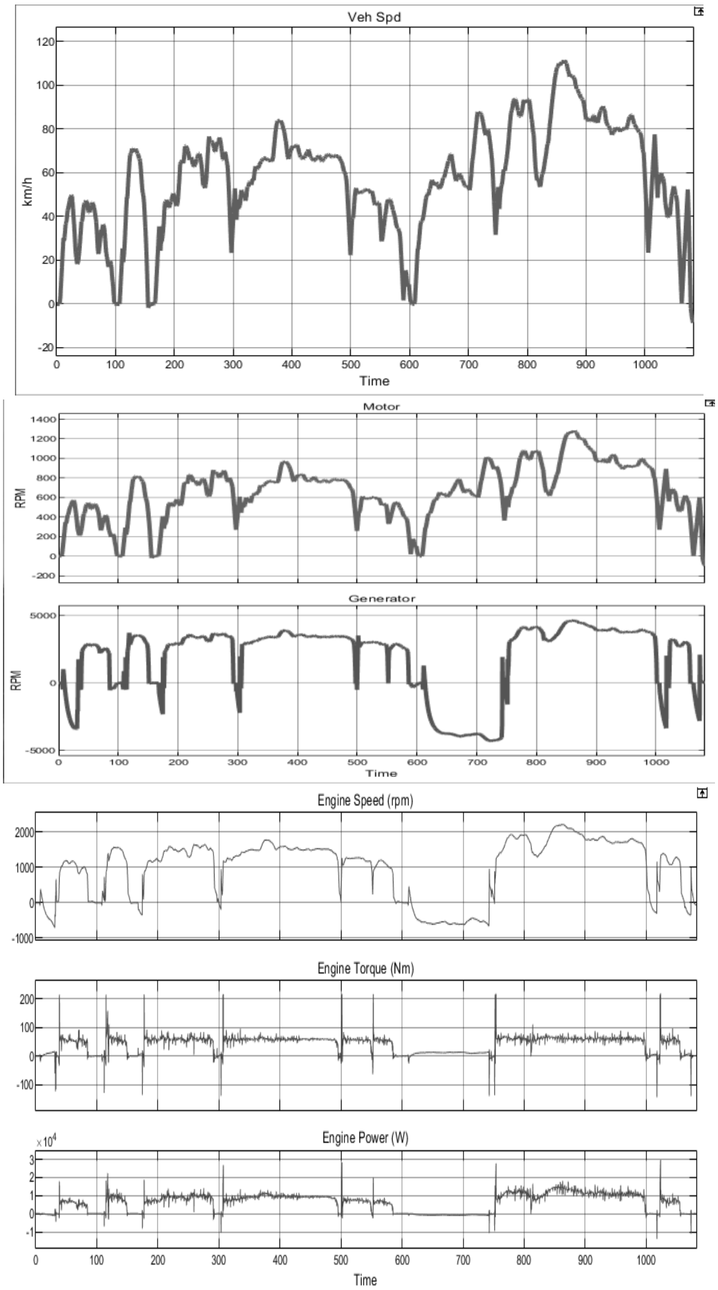

Figure 52 - ARTEMIS Rural on virtual test bench with AMPC

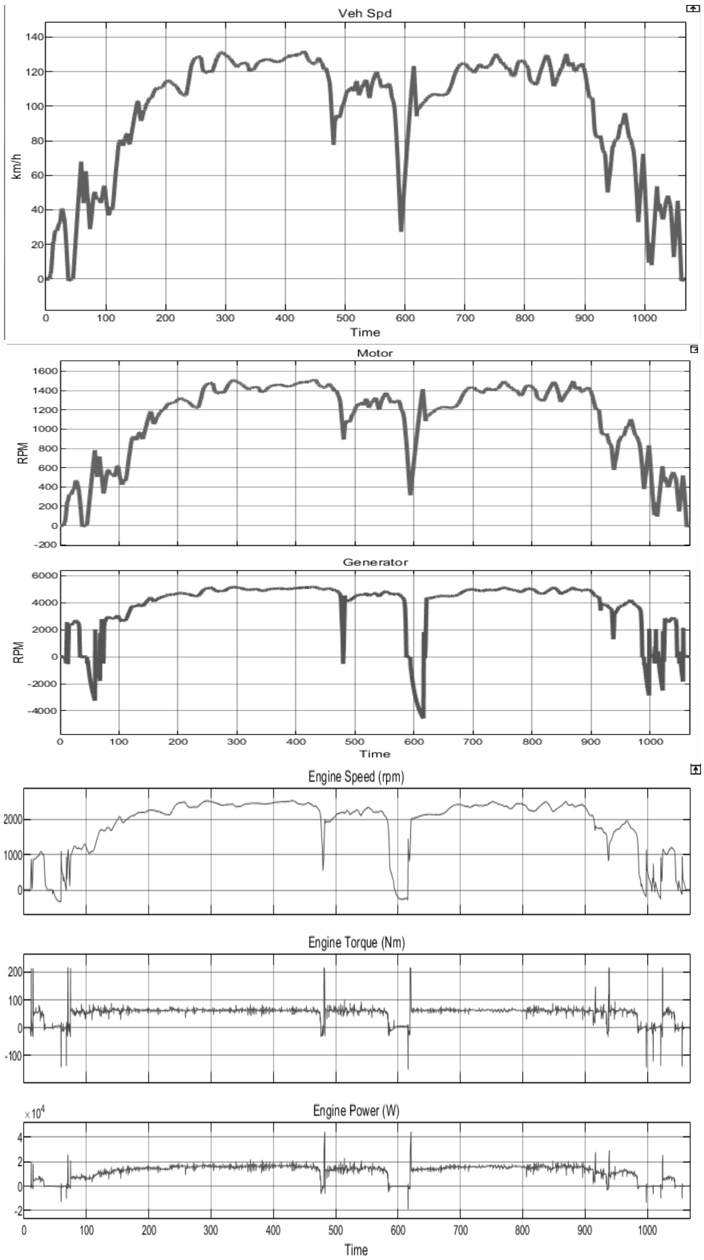

Figure 53 - ARTEMIS Motorway on virtual test bench with AMPC

Table 9 - Driving cycles with AMPC setup info

Driving Cycle	Setup Information		
	Time (s)	Distance (m)	Average Speed (km/h)
NEDC	1180	11023	33.6
WLTP	1477	23262	44.5
FTP-72	1369	12070	31.5
FTP-75	2474	17770	34.12
ARTEMIS Urban	993	4870	17.6
ARTEMIS Rural	1082	17272	57.5
ARTEMIS Motorway	1068	28735	96.9

Table 10 - Fuel consumption summary

Driving Cycle	Fuel Consumption (gr CO2/km)
NEDC	47,49
WLTP	50,95
FTP-72	52,81
ARTEMIS Urban	102,45
ARTEMIS Rural	32,48
ARTEMIS Motorway	16,74

Chapter 4. Conclusions

In this last Chapter, a summary of the thesis is drawn, and the major results and contributions of the research are presented. Besides, an outlooked vision is delineated, offering some new ideas to continue this work.

4.1. Outline

This thesis aims to study and develop intelligent test bench for the project of an electric system for traction of innovative vehicles.

To better understand the improvement area of the work, an initially background review regarding the market has been done, that is the main factor that guides the developments, and the scientific context for the work assignment. No less important are the hybrid vehicle configurations and the modelling, simulation, control and test run metric. After a brief introduction, these themes are presented in Chapter 1.

Chapter 2 goes into detail on the environment and methods studied and used for the research activities during the PhD. The test bench initially modelled, is the primary environment where the second case study was based. However, to have a complete system, the other parts was modelled. In the automotive industry, several techniques result in this modelling. Among the most current and with the most significant scientific value is the technology. XiL contains a set of advanced techniques that allow models, software and hardware to be integrated into the system loop. Then there is the part about evaluating the system. The answer comes precisely from the market. One of the main and most important factors is the assessment of fuel consumption and the value of emissions in the vehicle. From these parameters, it is possible understand if the system works correctly and if the models have the same performance as the real ones. To complete the whole system, it was necessary to develop a model of the vehicle that was as real as possible and included suitable control techniques.

In Chapter 3 of this thesis the simulations keep in consideration the real data from the environment and physical hardware and process; for this reason, is not limited to simulation and finally, the results are extended with the digital twin approach. This approach feeds real data into XiL systems and evaluates performance with them. Two case studies were analysed to achieve the aim of the thesis.

The former involves the development of an electric vehicle model that considers the specifications of an MHEV. Two control techniques, a fuzzy supervisor PID controller and an MPC controller, were analysed and implemented to compare the performances obtained. From tests on standard routes to evaluate performance in a more real and targeted way, a GPS sensor has been integrated. Verification and evaluation of the system is carried out with the value of emissions that are within the expected ranges.

The latter case study, on the other hand, takes up a simplified vehicle and proposes a more complex and extended system. A complete test bench is modelled and, with the engine in the loop technique, standard driving cycles are tested, including typical disturbances. Here an advanced control technique was implemented, and the emission values calculated. Since the model is non-linear, it was necessary to linearize it and use an online AMPC controller.

The main objectives were fully achieved during the PhD, and the synthesis presented in this thesis shows how, starting from the backgrounds and environments, it was possible to obtain a model of the actual vehicle with control techniques that allowed to increase its efficiency and improve its consumption by lowering emissions and testing it in real conditions thanks to the GPS sensor.

On the other hand, a complex model of the test bench has been made intelligent with advanced control techniques to make it able to adapt online to a real input and verify and validate the system by measuring fuel consumption and calculating emissions.

4.2. Outlook

In the pioneering generation of 48-volt mild hybrid vehicles, the activation and the mix of hybrid operating strategies will be based on impulses provided by the driver. If the steps off the accelerator pedal, for instance, Coasting and recuperation or a mix of the two will be initiated. This control principle, based upon a system response to a triggering impulse, is highly effective but is also subject to one limitation: By solely being responsive, some opportunities for saving fuel and harvesting kinetic energy are entirely missed or will only be exploited to a certain extent. One of many conceivable examples would be a speed limit zone to which the driver can only respond as soon as the traffic sign comes into sight. Other examples can be found in an unexpected crossing where the driver must yield to right, or in a downgrade the driver did not know about. During each of these situations, hybrid operating strategies could contribute to vehicle efficiency if the event was known in advance. So, the bottom line is that the driver's line of sight is often too short of exploiting the full potential of coasting, recuperation, and of electric boost or sailing. In future, this limitation can be eliminated by extending the horizon of the vehicle and adding a predictive element to hybrid control. To make this predictive control possible, the driver needs to be integrated into the process of controlling hybrid operation strategies. Therefore, EM not only activates the powertrain components optimally but also supports the driver in selecting an energy-optimal speed trajectory. One very effective way of doing this is to provide haptic signals to the driver's foot. To add this human-machine interface, the connected energy management car is equipped with an accelerator force feedback pedal. It can generate discrete signals to the driver, telling him when stepping off the gas would be ideal for saving fuel. In an initial step, energy consumption was reduced by 3% during cross-country driving with the 48-volt system by using static map information. After the driver releases the accelerator, the energy-optimum driving profile for the upcoming driving situation is activated. If the driver wishes to override the system suggestion, all he needs to do is step on the gas or the brake. For further energy-based optimization of the speed trajectory, up-to-date dynamic route information is useful, particularly for urban driving where conditions change rapidly. Relevant data can be provided using a vehicle connected to an intelligent backend via a dynamic electronic horizon. This algorithm makes information on traffic signs, dynamic speed limits, expected traffic light phases, and current traffic data available. One of the use cases would be to switch the vehicle powertrain to coasting when the car approaches a red traffic light and to use the last bit of the approach to add a deceleration phase with regenerative braking that brings the vehicle to a standstill in front of the traffic light. Likewise, the coasting phase can begin just before a section or a road with a speed limit. Depending on the altitude profile of the route as well as any bends, intersections, and traffic signs, this allows the driving strategy to be adapted to suit the route. To analyse the savings potential of EM, three functions named Smart Traffic Light Assist, Smart Curve Speed Assist, and Intelligent Deceleration Assist were developed and implemented in the demonstrator car. The demonstrator car with the Smart Traffic Light Assist was first demonstrated under real-world driving conditions.

In conclusion, electrification is the future of mobility. It may come along in various types, though. 48-volt technology has the potential to become the workhorse of mild hybridization. Owing to its simple integration and limited cost, it can be used in the mass volume segments where the scale effect is potentially enormous. If a large share of the world's vehicles were to save a two-digit percentage of fuel, the global benefit be highly welcome. Assuming that the integration depth of 48-volt systems and the systematic optimization on the vehicle level will increase, a growing number of 48-volt vehicles may be able to save upwards of 25% of fuel during urban driving in the future. Considering the global trend towards living in megacities, this makes a perfect fit between technology and the expected lifestyle of billions of people. Whether the combustion engine is here to stay or whether mild hybridization may "only be a matter of some decades of transition, 48-volt technology will establish itself as a versatile, modular and affordable contribution to modern individual mobility. This trend may well be accelerated further by the advent of auto- mated driving. Vehicles capable of taking over the driving task for a certain time will not only contribute to driving safety. Automated driving will also help to save fuel by increasing the total efficiency of a trip. In order to achieve this benefit, automated vehicles require electric energy to power actuators needed for functions such as automated steering. Providing the electric energy for this new demand is another potential contribution 48-volt technology can make. Once the energy content, weight and cost of high-voltage batteries reach a level that makes them truly mass-suitable, BEVs will develop into a solution not only for "the smooth asphalt surfaces in major cities" but also for "journeying across the land at high speeds". The future is going to be electric.

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