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Design of electric motorcycles using right-sizing criteria and framework definition for analysis and synthesis of driving cycles

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La vita è come una bicicletta. Si deve avanzare, per non perdere l'equilibrio.

Albert Einstein

Dedication

Dedicated to all my friends and colleagues whom I met in these years, and shared the journey with me. To all the great time spend to discuss and laughing, to all the hours of hard work, to the awesome experiences. To my beloved parents and siblings, thanks for their affection

DECLARATION

I hereby declare that this submission is my own work and, to the best of my knowledge and belief, it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at the University of Florence or any other educational institution, except where due references are provided in the thesis itself.

Any contribution made to the research by others, with whom I have been working at the University of Florence or elsewhere, is explicitly acknowledged in the thesis.

Adelmo Niccolai
31/03/2025

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ABSTRACT

The development of high-performance electric superbikes requires a comprehensive understanding of powertrain architectures, energy efficiency, and real-world riding dynamics. This thesis explores key aspects of superbike design, focusing on energy consumption and regeneration, drivetrain architecture, driving cycle synthesis, and powertrain optimization.

First, the vehicle dynamics were investigated, focusing on aspects of energy consumption. Then the vehicle dynamics was described to design the powertrain power demand. The work introduces models to estimate the tire slip loss, longitudinal and lateral. Interestingly, when examining lateral power slip loss, motorcycles exhibit reduced loss because the lateral force largely results from camber thrust, as opposed to lateral tire deformation noted in cars and trucks.

Second, real-world data (≈ 400 km) were collected and analyzed to characterize superbike riding. Analysis highlighted the misrepresentation of the standard cycles to represent the sport motorcycle ride, for example, the relative positive acceleration (RPA) of the World Motorcycle Test Cycle (WMTC) is 0,15, while the data RPA value is 0,71. In particular, the characteristic acceleration ($\tilde{a}$) and aerodynamic speed (V_{aer}) well correlate with the consumption. Furthermore, a novel methodology for synthesizing high-fidelity driving cycles based on real-world riding data was developed. By leveraging a 3D Markov Chain approach that captures and replicates the aggressive riding behavior of sport motorcycles, to address the limitations of conventional approval cycles. The synthesis method is based on longitudinal speed and acceleration, and road slope. Data and the constructive method were used to synthesize the Sport Motorcycle Driving Cycle (SMDC), which was significantly shorter than the reference data with 35,8 km (-90,7%), and the error on the vehicle energy consumption was -0.34%.

The consumption of a constant-speed gearbox was investigated, focusing mainly on load-independent losses. Two different gearbox and powertrain solutions are characterized through test bench experiments, running them under free-driving conditions and no-load tests. A comparison of these powertrain solutions in terms of consumption for the same motorcycle model under different speed profiles (WMTC, LA-4) was conducted. The results show the energy losses and provide information for defining drivetrain components and architectures for sport motorcycles.

The impact of regenerative braking architectures, comparing rear-wheel and two-wheel regenerative strategies under varying road slopes (from -5° to 5° with 0.5° step increment), speed profiles (WMTC, experimental data), and braking distributions (5 different repartition strategies). The findings highlight the potential for energy recovery and its implications for range extension.

Finally, an optimization framework was presented for the powertrain design of an all-wheel-driven electric superbike. By jointly optimizing force distribution, gear ratios, and component sizing, achieving significant energy consumption reductions while maintaining performance and adherence constraints. The tool was applied to two power axle distribution strategies and three driving cycles (UDDS, WMTC, and Sport). The adherence strategy tends to maximize the tire adherence, while the optimal strategy tends to minimize the rear and front motor losses. Significant differences in vehicle mass, motor peak power, and

consumption were found between the two strategies. The consumption was always lower for the optimal strategy repartition than the adherence strategy, going from -4.7% for the WMTC part 3 to -22.4% for the Sport cycle.

The outcomes of this research contribute to the development of next-generation electric superbikes, providing valuable insights into regenerative braking strategies, drivetrain architectures, and powertrain optimization for enhanced efficiency and performance in real-world conditions.

Keywords: Synthetic driving cycles, Real-world superbike data and energy consumption, Motorcycle electrification and sport driving cycle, Powertrain Optimization, Optimal Propulsive Blending Strategy

PROPOSITIONS

Motivation

- Reduce the vehicle emissions and consumption
- Electrification of road sport motorcycle

Original contribution

- Developed the Sport Motorcycle Driving Cycle
- Set a Framework for jointly optimizing the powertrain and propulsive blending strategy
- Investigated the all-wheel-driven motorcycle architecture
- Clustered and analyzed real-world data of sport motorcycles

Open questions

- Sport electric motorcycle ride behavior
- Thermal powertrain management
- Powertrain model cost
- Battery losses and degradation

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SYNOPSIS

This PhD thesis focuses on the sizing of the powertrain for high-performance electric motorcycles, addressing both the technical challenges and the optimization opportunities available in this emerging field. The research is structured into eight chapters, each contributing to a comprehensive understanding of electric motorcycle powertrain design.

Chapter 1 provides an introduction to electric vehicles, covering the electrification of road vehicles, the fundamentals of electric vehicle technology, their limits, and an analysis of the electric motorcycle market and its adoption trends worldwide.

In Chapter 2, the state-of-the-art is reviewed, detailing driving cycles, benchmarking of market sold electric motorcycles, energy consumption flow, vehicle modeling, energy sources for electric vehicles, utilization of the electric machine and driveline for electric vehicle traction.

Chapter 3 summarizes the key original contributions of this work, laying the foundation for novel methodologies and design strategies.

Chapter 4 describes vehicle dynamics, both longitudinal and lateral, with a particular focus on energy consumption aspects.

Chapter 5 describes the synthesis of driving cycles and the development of the Sport Motorcycle Driving Cycle (SMDC), tailored to capture the performance requirements of high-performance electric motorcycles, including the altitude profile. Chapter 6 analyzes the powertrain losses, providing a detailed evaluation of where and how energy is dissipated and its influence on consumption.

Finally, Chapter 7 explores vehicle optimization, specifically examining the influence of brake blending and the joint optimization of battery, motor, and gear ratio for a two-wheel-driven superbike, culminating in recommendations for enhanced performance and efficiency. Chapter 8 concludes the thesis by summarizing the findings, discussing their implications, limits, and suggesting hints for future research.

NOMENCLATURE

Acronyms

AFM	Axial Flux Motor
AFPM	Axial Flux Motor Permanent Magnet
AWD	All-Wheel-Driven
BEM	Battery Electric Motorcycle
BEV	Battery Electric Vehicle
BMS	Battery Managment System
BVM	Backward Vehicle Model
CoG	Center of Gravity
CP	Characteristic Parameter
CVT	Continuous Variable Transmission
DC	Driving Cycle
DoD	Depth of Discharge
ECV	Equivalent Circuit Model
EDLC	Electrochemical Double Layer Capacitor
EMI	Electromagnetic Interference
EOL	End of Life
EREV	Extended-Range Electric Vehicle
ESS	Energy Storage Systems
EV	Electric Vehicle
FC	Fuel Cell
FCEV	Fuel Cell Electric Vehicle
FESS	Flywheel Energy Storage Systems
FVM	Forward Vehicle Model
GHG	Greenhouse gas

HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
ICEV	Internal Combustion Engine Vehicle
LCA	Life Cycle Assessment
LDV	Light-Duty Vehicle
LIB	Lithium-ion battery
MCMC	Markov-Chain Monte-Carlo
MT	Micro-Trip
OCV	Open Circuit Voltage
PV	Performance Value
RBS	Regenerative Braking System
RFM	Radial Flux Motor
RPA	Relative Positive Acceleration
RUL	Remaining Useful Life
SAPD	Speed Acceleration Probability Distribution
SC	Supercapacitors
SMDC	Sport Motorcycle Driving Cycle
SMPM	Synchronous Motor Permanent Magnet
SoC	State of Charge
SoE	State of Energy
SoF	State of Function
SoH	State of Health
SoP	State of Power
SOS	State of Safety
SPMSM	Surface Permanent Magnet Synchronous Machine
SRM	reluctance motor
SynRM	Synchronous Reluctance Motors
TPM	Transition Probability Matrix
TTW	Tank-to-Wheel
UC	Ultracapacitor

UDDS	Urban Dynamometer Driving Schedule
VSP	Vehicle Specific Power
VTM	Vehicle-To-Miles
WMTC	World Motorcycle Test Cycle
WTT	Well-to-Tank
WTW	Well-to-Wheel

Greek symbols

α	sideslip angle	[rad]
β	propulsive bias	[-]
ϵ_y	camber reduction factor	[-]
η	efficiency	[-]
η_b	battery efficiency	[-]
η_{gb}	gear box efficiency	[-]
η_{inv}	inverter efficiency	[-]
γ	camber angle, gear ratio	[rad, -]
μ	tire adherence coefficient, pitch angle	[-, rad]
ω	angular speed	[rad/s]
ϕ	roll angle	[rad]
ψ	yaw angle	[rad]
ρ	air density	[kg/m ³]
θ	road slope	[rad]
θ_{max}	maximum climbing road slope	[deg]
φ_t	turn slip	[rad/m]
ξ_{max}	maximum battery SoC	[-]
ξ_{min}	minimum battery SoC	[-]
ζ	regenerative ratio	[-]

Latin symbols

$\bar{E}$	specific energy	[N]
a_1	longitudinal distance from the front tire to CoG	[m]
a_2	longitudinal distance from rear front tire to CoG	[m]

A_f	cross section front aerea	$[m^2]$
$C_{\gamma,0}$	tire camber stiffness	$[Nrad^{-1}]$
$c_{\gamma,0}$	normalized tire camber stiffness	$[rad^{-1}]$
C_d	drag coefficient	$[-]$
$c_{k,0}$	normalized tire longitudinal stiffness	$[rad^{-1}]$
c_{rr}	tire rolling resistance coefficient	$[-]$
$C_{x,0}$	tire longitudinal stiffness	$[Nrad^{-1}]$
$C_{y,0}$	tire cornering stiffness	$[N]$
C_M	pitching moment coefficient	$[-]$
e_x	longitudinal arm	$[m]$
e_y	camber arm	$[m]$
F_{air}	aerodynamic force	$[N]$
F_{gr}	road grade force	$[N]$
F_{rr}	tire rolling resistance	$[N]$
F_{trac}	tractive force	$[N]$
F_x	lateral force	$[N]$
F_x	longitudinal force	$[N]$
F_z	vertical load	$[N]$
g	gravitational acceleration	$[ms^{-2}]$
I_z	yaw moment inertia	$[kgm^2]$
k	longitudinal practical slip	$[-]$
k_A	axial scaling factor	$[-]$
k_R	radial scaling factor	$[-]$
K_z	tire vertical stiffness	$[Nm^{-1}]$
m	mass	$[kg]$
M_x	overturning moment	$[N\ m]$
M_z	self-aligning moment	$[N\ m]$
P_{aux}	auxiliary power	$[W]$
r	yaw rate	$[rads^{-1}]$
R_e	effective rolling radius	$[m]$

R_l	effective rolling radius	[m]
R_l	loaded wheel radius	[m]
r_w^f	front wheel radius	[m]
r_w^r	front wheel radius	[m]
t_{acc}	acceleration time	[s]
t_p	pneumatic trail	[m]
v_f	final acceleration speed	[ms ⁻¹]
v_{max}	top speed	[ms ⁻¹]
v_{min}	minimum climbing speed	[ms ⁻¹]
v_x	longitudinal speed	[ms ⁻¹]
v_y	lateral speed	[ms ⁻¹]
W	weight force	[N]
w	cost function weight	[-]
w_b	wheelbase	[m]
D	final acceleration speed	[ms ⁻¹]
h	distance or riding range	[km]

Subscripts

f	front
r	rear

Superscripts

f	front
r	rear

1. INTRODUCTION

1.1 Electric vehicle

1.1.1 Vehicle electrification

In 2021, transportation accounted for 24,34 % (7,63 billion t) of total CO₂ emission [55]. Figure 1.1 shows the emission of CO₂ for different sectors. The transportation sector is the second cause of greenhouse gas emissions.

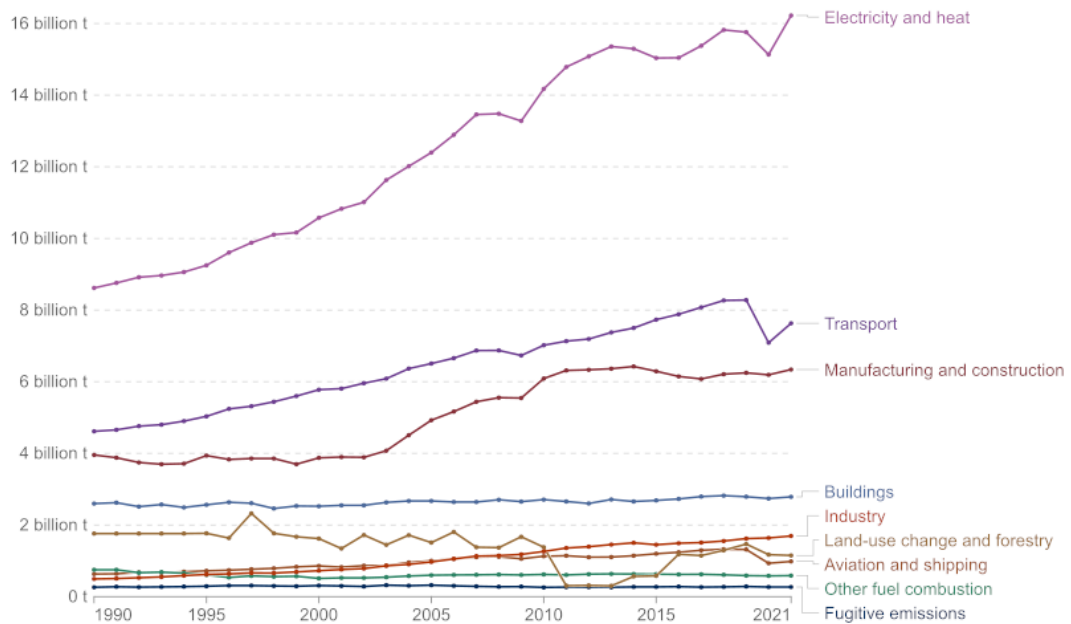


Figure 1.1: World CO₂ emissions by sector, 2021, from [56].

The electrification of transport is considered a key strategy in the transition to sustainable energy, with the primary goal of reducing greenhouse gas (GHG) emissions and air pollution [86, 234, 318]. However, the overall environmental impact of transport electrification is complex and depends on several factors, including the source of electricity used to charge electric vehicles (EVs) and the entire vehicle life cycle, from production to disposal [66, 119, 220, 234].

In many cases, EVs can produce fewer greenhouse gas emissions than internal combustion engine vehicles (ICEVs), especially if the electricity is generated from renewable sources. Studies have shown that EVs can emit significantly less CO₂ than conventional cars [86, 186, 226]. Even when electricity comes from fossil fuel power plants, the higher efficiency of energy generation and electric motors can lead to a reduction in GHG emissions compared to distributed internal combustion engines [134, 242]. In 2014, the EU's average CO₂ emissions (well-to-tank) tallied up to 178 g/km for gasoline engines and 145 g/km for diesel engines [246], respectively. In 2021, a comparison between conventional and electric vehicle emissions in the European context found that conventional vehicles are responsible for an average specific CO₂ equivalent emission of 187 g/km, and the battery electric vehicles (BEVs) revealed a CO₂ equivalent emission of 109.6 g/km, which represents about 58.6% of the traditional ICEV. In a similar case study in Istanbul, authors estimate that the WTW (well-to-wheel) emission of CO₂ for ICEV and EV was 183,4 g/km and 73.9 g/km [221].

EVs do not produce direct exhaust emissions, which can significantly improve air quality in urban areas, reducing exposure to harmful air pollutants [234]. This is particularly relevant considering that transportation is one of the main sources of environmental degradation globally [226].

Electric motors are generally more efficient than internal combustion engines in converting energy into movement [7]. Internal combustion engine vehicles (ICEVs) have a well-to-wheel efficiency between 11-27% for gasoline engines, and 25-37% for diesel engines, while electric vehicles have a WTW efficiency from 40 to 70%, depending on the energy mix. In the other cases (natural gas power plant, coal-fired plant, and diesel power plant), the efficiency between electric vehicles and conventional vehicles is similar. Direct electrification of transport massively reduces energy losses on the demand side by replacing inefficient combustion processes with more efficient electric motors. The electrification of transport can facilitate the integration of intermittent renewable energy sources into the electrical grid by using vehicle batteries as energy storage systems [23, 318]. Smart charging of EVs, particularly with an increasing share of renewable energy, can significantly reduce emissions [226].

The environmental impact of electric vehicles (EVs) and conventional internal combustion engine vehicles (ICEVs) varies significantly when considering the entire life cycle, from cradle to grave [215]. For ICEVs, the usage phase is generally the most impactful in terms of greenhouse gas emissions due to the combustion of fossil fuels [232]. However, vehicle production also contributes significantly to the overall environmental impact. In contrast, for electric vehicles, the production phase plays a more significant role due to the energy and materials required for battery manufacturing, which involves the extraction of minerals and metals with potential environmental consequences [232]. Figure 1.2 shows the global warming potential comparison for ICE, hybrid electric vehicle (HEV), and battery electric vehicle (BEV).

Therefore, while ICEVs concentrate most of their impact during the usage phase, EVs have a higher initial impact during production, but their overall life cycle impact can be lower, especially with a decarbonized energy mix. Both vehicle types also require consideration of the end-of-life phase, including the treatment and disposal of components and, in the case of EVs, their batteries [118]. A comprehensive life cycle assessment (LCA) is essential to accurately compare the overall environmental impact of different propulsion technologies.

On the other hand, EVs have potential drawbacks and environmental impact considerations, like emission shifting. Electrification may simply shift emissions from vehicle exhaust pipes to power plants [127, 226, 234]. If electricity is primarily generated from fossil fuels, the overall environmental impact may be only marginally better or even worse in some categories [220]. For example, a study in Poland found that under average conditions of the Polish power generation system, charging EVs results in higher exhaust gas production than

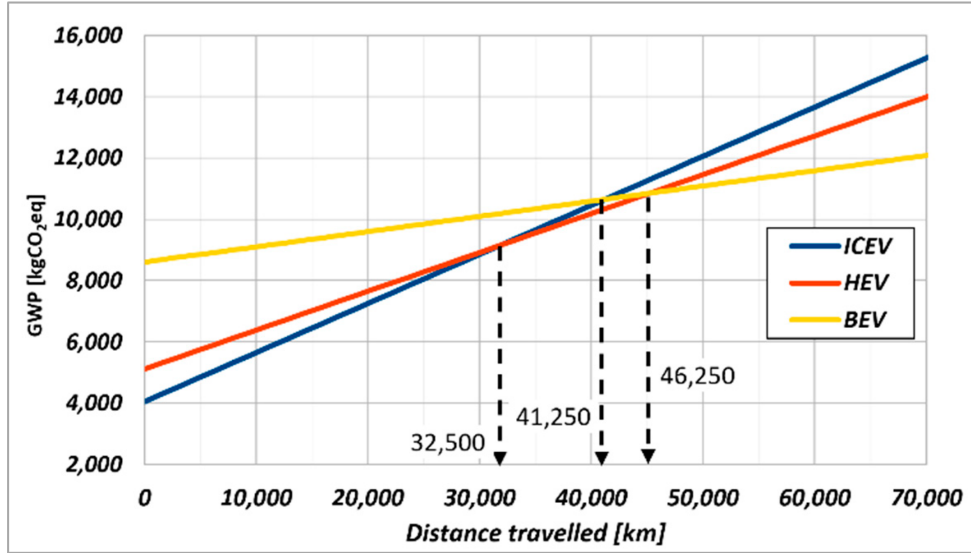


Figure 1.2: Global warming potential (GWP) comparison as a function of the lifetime distance traveled, from [232].

ICE cars [8]. In Xian, China, a study found that EV development from 2021 to 2035 could exacerbate SO₂ emissions despite reducing thermal power generation [66].

The production, use, and disposal of EV batteries have significant environmental impacts, including the extraction of minerals and metals (such as lithium, copper, and aluminum), which can cause pollution and resource depletion [119, 226]. The battery disposal phase can also release toxic metals, organic compounds, and GHGs [226]. Life cycle assessment studies show that EV production can be substantially more environmentally intensive than that of conventional vehicles, leading to potential increases in human toxicity, freshwater ecotoxicity, freshwater eutrophication, and metal depletion [119].

To properly compare environmental impacts, it is necessary to consider well-to-wheel efficiency, which includes fuel extraction, production, transportation (or electricity generation and transmission), and vehicle use. The tank-to-wheel efficiency of EVs is generally higher than that of gasoline vehicles, but the overall efficiency heavily depends on the electricity source.

For both electric and hydrogen vehicles, it is essential to consider the environmental impact of building and operating charging infrastructure as well as hydrogen production, storage, and distribution facilities [91].

The integration of EVs with renewable energy sources is crucial to maximizing the environmental benefits of transport electrification. When EVs are powered by electricity from low-carbon sources such as hydropower, wind, or solar energy, their overall environmental impact is significantly lower than that of conventional vehicles [234]. A scenario with high EV penetration and a high rate of thermal energy generation will require specific coupling conditions to achieve carbon emission peak targets.

The environmental impact of transport electrification varies significantly depending on a country's or region's electricity generation mix. For example, in Norway, where a very high share of electricity is produced from hydropower, the environmental benefits of EVs are more pronounced [86]. Conversely, for a region highly dependent on coal for electricity production, the benefits may be lower or even negative for some impact categories.

Electrification can be direct or indirect. Direct electrification, such as the adoption of battery electric vehicles (BEVs) for road and rail transport, leads to overall efficiency improvements. Indirect electrification, which involves the use of synthetic fuels based on renewable

electricity (e-fuels) for sectors like maritime and air transport, where direct electrification is more challenging, results in additional energy losses during the fuel synthesis process [28].

Reducing local air pollution through transport electrification can have significant public health benefits, lowering respiratory diseases and other health issues associated with vehicle pollutant exposure [66]. However, it is also necessary to consider the health impact of emissions from power plants and battery production [118].

In conclusion, transport electrification has the potential to significantly reduce greenhouse gas emissions and improve air quality, contributing to environmental sustainability. However, the actual environmental benefits strongly depend on the decarbonization of the energy sector and sustainable management of the entire life cycle of electric vehicles, particularly their batteries. Promoting renewable energy sources to power EVs and adopting circular economy approaches for batteries are crucial to minimizing negative impacts and maximizing the advantages of transport electrification. Appropriate policies and incentives are necessary to drive this transition toward cleaner and more sustainable mobility.

1.1.2 Fundamentals and challenges of electric vehicles

An electric vehicle (EV) is defined as a vehicle equipped with a portable energy source, either electrochemical or electromechanical, where the traction effort is provided solely by an electric motor [135]. There are several types of electric vehicles, including all-electric vehicles (AEV or BEV), which use only batteries as an energy source; hybrid electric vehicles (HEV), which combine an electric motor with an internal combustion engine; and extended-range electric vehicles (EREVs). The main technologies for electric vehicles include energy storage systems such as batteries (primarily lithium-ion batteries), ultracapacitors, flywheels, and fuel cells; electric motors (such as brushed DC motors, three-phase AC motors, reluctance motors, and permanent magnet synchronous motors); power electronics required to control the energy flow between the energy source and the motor, including DC-DC converters and AC-DC inverters, and on-board charger. Figure 1.3 shows a detailed diagram of an electric vehicle system, illustrating the interaction between its main components: motor, controller, energy source, and transmission, for a passenger car.

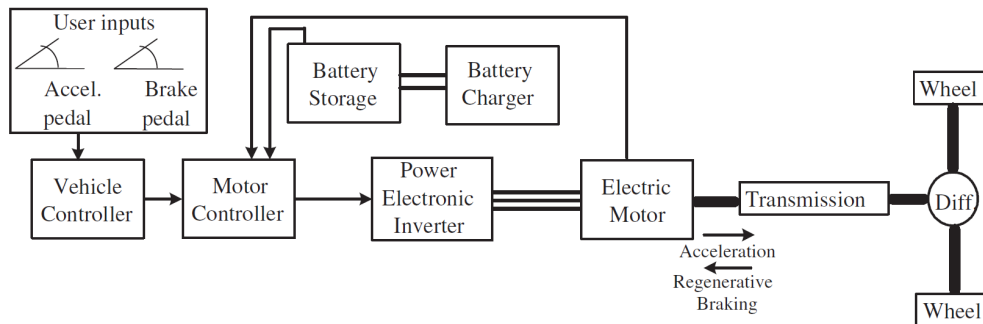


Figure 1.3: Major electrical components and choices for an EV system, from [136].

Electric vehicles offer a certain degree of flexibility due to their architecture and the various components that can be combined. For example, the ability to use different energy sources such as lithium-ion batteries, supercapacitors, and fuel cells provides flexibility in the design of energy storage systems (ESS) to meet different power and energy requirements. Hybridization of these ESS can improve ESS lifespan and overall performance [311]. Additionally, the absence of direct mechanical wiring between certain components allows greater freedom in positioning components within the vehicle, utilizing otherwise unused spaces. Furthermore, in electrified traction systems, there is an opportunity to simplify the

transmission system, reduce the requirements for individual components such as the starter device or clutch needed for conventional engines, or use fewer gear ratios.

Despite their flexibility, electric vehicles have intrinsic limitations in their technology. Energy storage systems (ESS), in particular, face significant challenges related to safety, size, cost, and overall management [116]. The trade-off between power and energy in batteries can result in suboptimal battery packs. It is crucial to optimize power distribution among different ESS under complex driving conditions. Additionally, SiC-based power modules present challenges related to packaging, thermal management, electromagnetic interference (EMI), and transient dV/dt immunity [311]. Batteries have limited power and energy capacity, a finite cycle life, and are sensitive to temperature [75]. Electric machines also experience variations in power and efficiency depending on speed, torque, and temperature. While at high speeds, AC motor control systems may reach insurmountable physical limits [76]. The weight and size of energy storage units remain significant constraints, and accurately predicting power impact on performance and battery lifespan can be limited by certain methodologies. Figure 1.4 shows the mass and volume for a 100 km range for different sources of energy. High-torque electric motors can be bulky and heavy, requiring high currents, while the use of multi-ratio transmissions may cause traction interruptions.

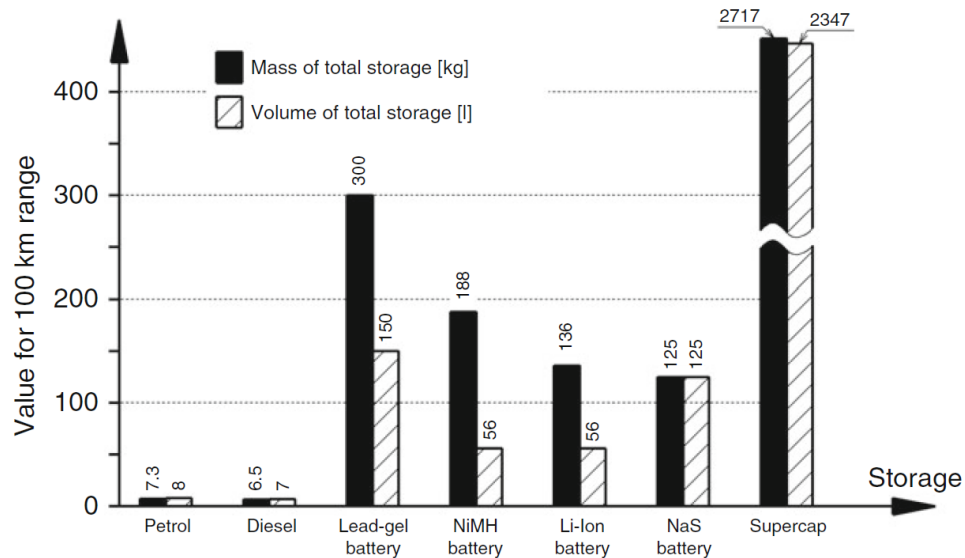


Figure 1.4: Mass and volume of different storage systems for 100 km range, from [284]. Based on typical consumption values, the mass and volume of the respective entire storage system are shown. The entire storage system includes the battery trough, battery management, and cooling.

Although a high energy conversion efficiency of electric vehicles, the low energy density of electrochemical sources results in a lower net energy density for the vehicle. For example, fossil fuels have an energy density between 12200-12800 Wh/kg, and lithium-ion cells between 180-250 Wh/kg. Therefore, an ICE vehicle with a typical efficiency of 20% has a net density energy around 2400-2500 W/kg. In contrast, an electric vehicle, even with 80% efficiency, achieves a net energy density of just 144-200 Wh/kg, which is over ten times lower. So the high efficiency of electric vehicles is not enough to reach values similar to fossil fuels' net energy density. Figure 1.5 shows the net energy density for several energy sources depending on standard propulsion.

The lower values for the hydrocarbons engine in Figure 1.5 are obtained by standard combustion engines, while the upper values (grey bars) are obtained with a not yet standard engine like hybrid-electric propulsion, downsized-supercharged gasoline engine systems, etc.

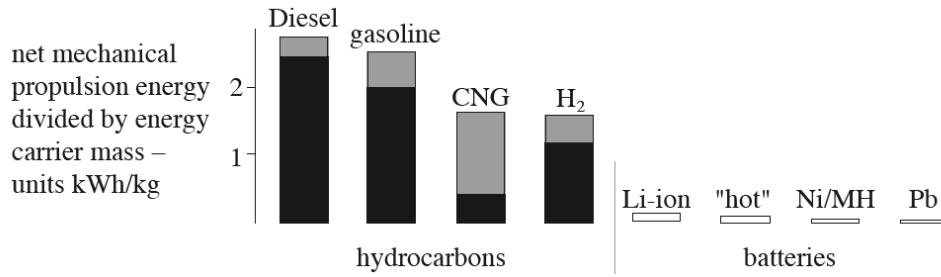


Figure 1.5: Estimates of the net energy density of several on-board energy carriers, from [114]. CNG stands for Compressed Natural Gas.

Electrical insulation is a primary aspect in the design of electric vehicles to ensure safety, given the presence of high-voltage systems, typically around 400 V [196]. Galvanic isolation, often implemented through transformers in DC/DC converters and battery chargers, is used to create a physical and electrical barrier between high- and low-voltage circuits, protecting users from the risk of electric shocks. Isolation monitoring devices are integrated to continuously check for dangerous current leakages to the vehicle chassis. In charging systems, insulation between the vehicle and the electrical grid is also crucial. Regarding magnetic insulation, it is inherently present in components such as transformers and electric motors, where magnetic fields are confined to ensure efficient operation and minimize electromagnetic interference (EMI) with other vehicle systems or external devices [196]. Electromagnetic compatibility (EMC) is a critical consideration for the entire electric vehicle, requiring the management and potential shielding of electromagnetic fields to prevent interference and ensure the proper functioning of all electronic components [87].

Electric vehicles (EVs) exhibit notable differences in noise, vibrations, and heat generation compared to internal combustion engine vehicles (ICEVs). EVs are generally quieter than ICEVs due to the absence of combustion processes and fewer moving parts [121]. However, this reduction in powertrain noise makes other sources, such as tire-road interaction and wind noise, more perceptible. Studies have shown that while EVs reduce overall noise levels, the prominence of these secondary noise sources can affect the perceived acoustic comfort [128]. The simplified architecture of EVs leads to reduced vibration levels compared to ICEVs. Nevertheless, the increased weight of EVs, primarily due to battery packs, can influence the dynamic behavior of the vehicle. Research indicates that this added mass affects the ride comfort and necessitates the development of specialized suspension systems to mitigate vibrations effectively. Furthermore, electric motors in EVs can introduce high-frequency vibrations, particularly during rapid acceleration or deceleration [157]. EVs are more efficient in converting energy into motion, resulting in less waste heat compared to ICE vehicles. This reduced heat generation affects the design of thermal management systems, necessitating innovative approaches to maintain optimal operating temperatures for components like batteries and power electronics. Thus, the thermal management of battery systems is critical to maintain performance and longevity, necessitating adequate approaches for components like batteries and power electronics.

Designing electric motorcycles presents significant challenges concerning space and weight, primarily due to the integration of energy storage systems. The batteries required to ensure adequate range are often bulky and heavy, posing a problem for vehicles characterized by compact dimensions like motorcycles. Figure 1.6 shows the frame and components of an electric motorcycle. The integration of battery packs within the chassis necessitates innovative design approaches to optimize space utilization without compromising the vehicle's structural integrity or performance [5]. Furthermore, the additional weight of these batteries

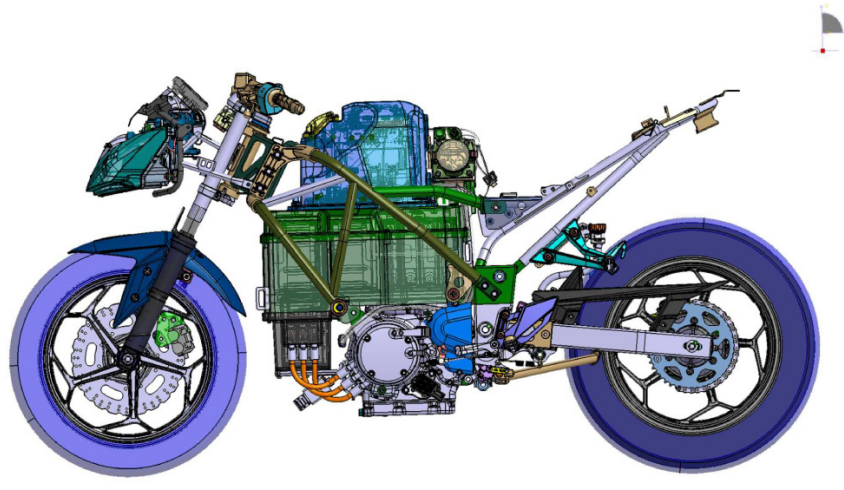


Figure 1.6: Design of the prototype EV-MC from[191].

can negatively impact the motorcycle's handling and stability. To address these challenges, some designs explore the use of hub motors integrated into the wheels. However, this configuration increases unsprung mass, which can adversely affect ride quality and handling [9]. The increased unsprung mass makes the wheels less responsive to road irregularities, potentially compromising both comfort and safety. Therefore, while hub motors offer packaging advantages, their impact on vehicle dynamics must be carefully considered.

In summary, the design of electric motorcycles requires a delicate balance between implementing necessary energy storage and maintaining optimal vehicle dynamics. Innovative chassis designs and careful consideration of component placement are essential to address the spatial and weight challenges inherent in electric motorcycle development.

1.2 Electric motorcycle overview

1.2.1 Motorcycle market

Motorcycles can be divided into segments, emphasizing features and targets like rider posture, handling, etc. According to [240], twelve main types of motorcycles classify the various motorcycle delineations. These latter types are: sport, standard/naked, cruiser, touring, adventure touring, sport touring, scrambler, dual sport, motard/supersport, dirt bikes, motocross, trials, and scooter. Sport motorcycles are designed for both roads and racing, featuring an aerodynamic rider seat that allows lateral movement during cornering. In the case of internal combustion engine sport motorcycles, medium to larger engine displacements (600 cc -1000 cc or more) are also referred to as supersport and hypersport, respectively.

The global motorcycle market is quite large, with 61.8 million sales, and revenue expected to reach US\$ 154.04bn in 2025, with an annual growth of 3.42%, resulting in a projected market volume of US\$ 176.25bn by 2029 [270]. In 2023, 9.9 million electric motorcycles were sold worldwide [193], with China accounting for more than 80% of the total sales. Figure 1.7 shows the worldwide motorcycle market in 2018, share by region and by motorcycle type.

The Asian continent has the highest motorcycle market share (57%), and 60% of the vehicles are motorcycles. This latter aspect can be understood due to the different motorcycle use across the world, especially between developed and developing countries. In large cities (particularly European countries), the motorcycle is used for commuting, while in other de-

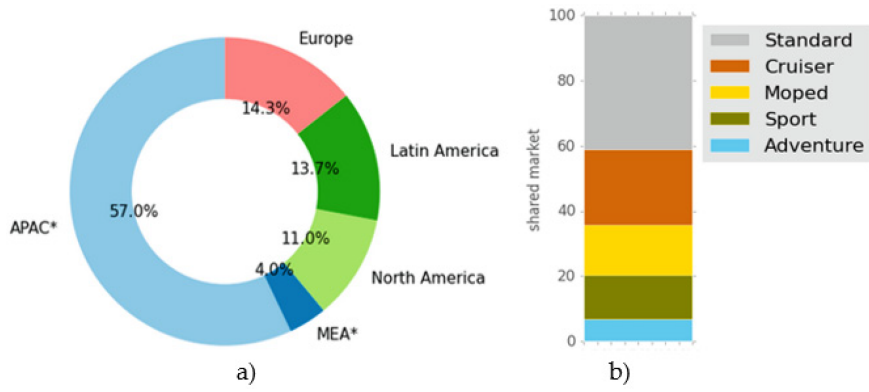


Figure 1.7: **a** Global motorcycle market share by region. **b** Global motorcycle market share by type. * APAC: Asia-Pacific. MEA: Middle East and Africa. Figure from [37].

veloped countries (such as the US and Canada), touring is more common than commuting [120]. In emerging countries, motorcycles are largely used as a means of mobility, and most motorcycles are low and medium engine capacity motorcycles [211]. In developed countries, bigger motorcycles are often ridden solo, whereas in developing nations, smaller motorcycles and scooters regularly carry passengers and come equipped with numerous add-ons for transport, delivery, vending, and passenger services. In high-income nations like the United States, Canada, Australia, and New Zealand, pleasure plays a major role [247]. Conversely, in countries with lower and middle incomes, such as Indonesia, Mexico, the Philippines, and Thailand, employment or entrepreneurship matters more. In regions plagued by heavy traffic, user-friendliness is crucial. Additionally, cost-efficiency is a key consideration in numerous low- to middle-income countries. Figure 1.8 illustrates the number of motorcycles for countries; in India, there are 31,31% of the global motorcycles.

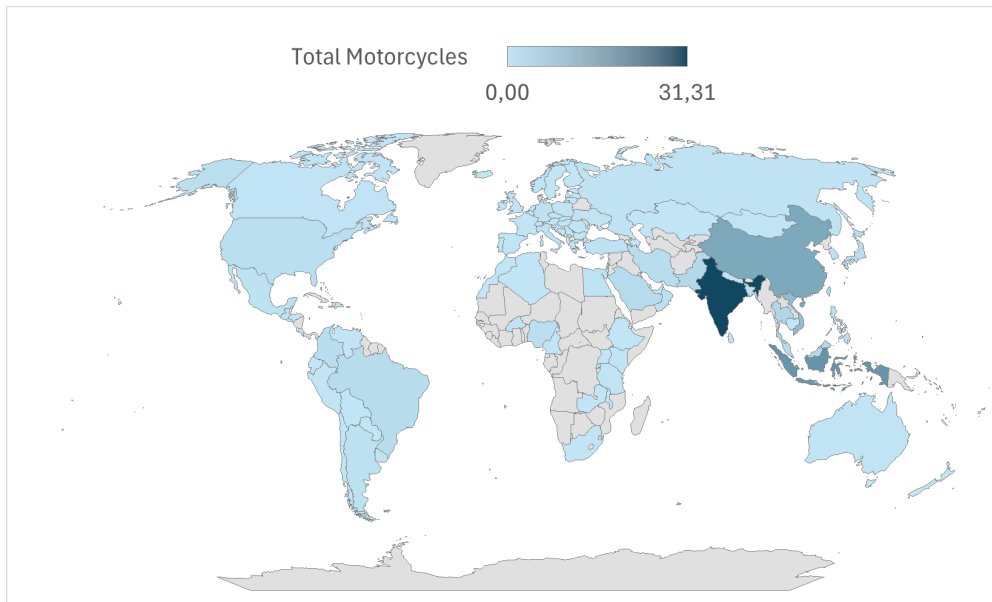


Figure 1.8: Motorcycle by countries, adapted from [307].

India, China, and the countries of the Association of Southeast Asian Nations (ASEAN) represent the largest markets for two and three-wheeler vehicles (2/3Ws) worldwide [137]. In 2023, sales of 2/3Ws in these regions, including both electric and internal combustion engine (ICE) powertrains, reached 19 million units in India, 17 million in China, and 14 million in ASEAN countries. Among ASEAN nations, Indonesia, Vietnam, the Philippines,

and Thailand stand out as the largest markets, where 2/3W sales significantly exceed those of light-duty vehicles (LDVs), underscoring their importance in the region [137]. Similarly, in India, there are 157 2/3W vehicles per 1,000 people, compared to just 35 passenger cars per 1,000 people. Figure 1.9 shows the 2/3W sales and sales share by geographic region from 2015 to 2023.

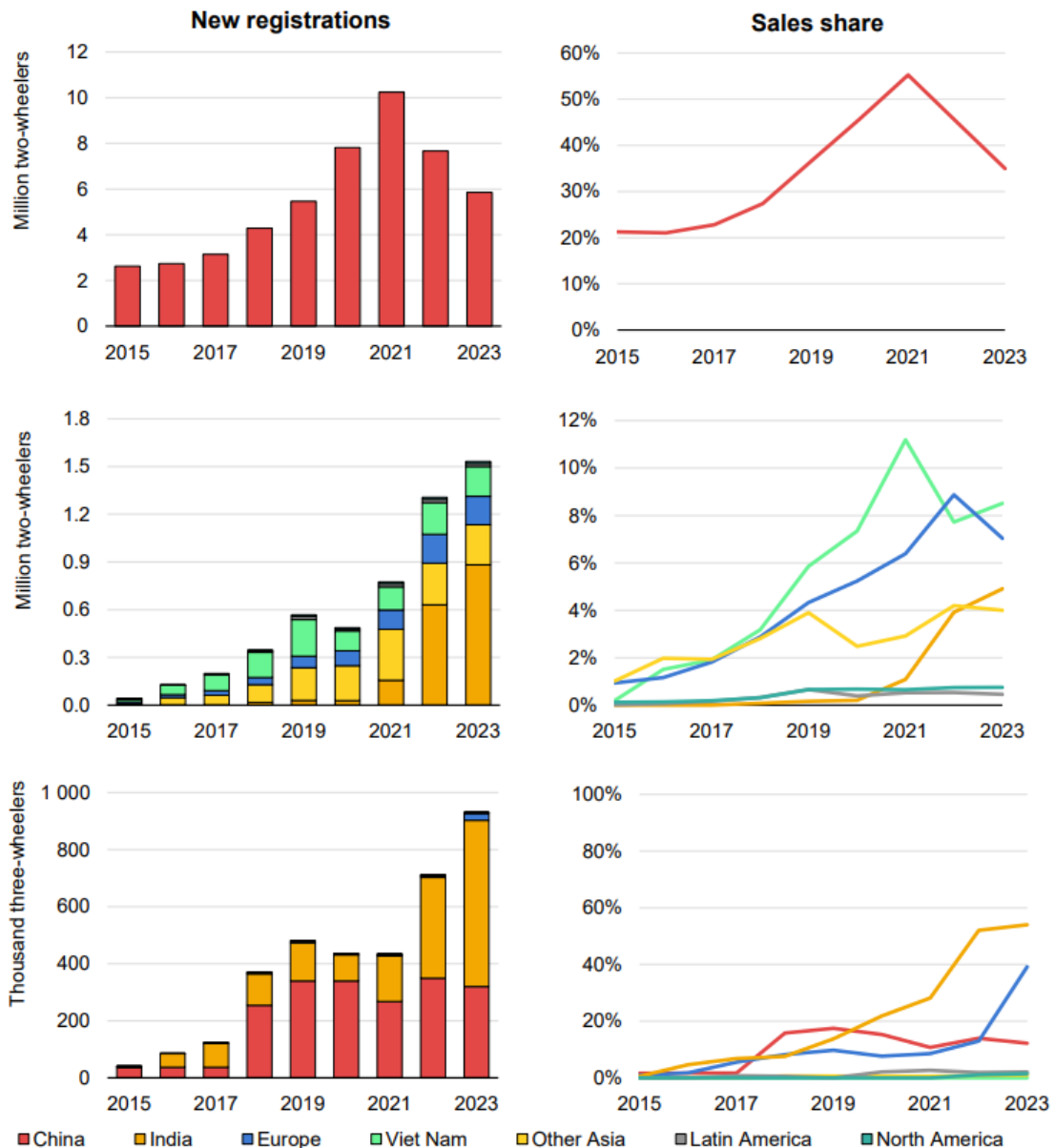


Figure 1.9: Electric two- and three-wheeler sales and sales share by region, 2015-2023, from [137].

Although the overall 2/3W markets in Latin America and Africa are smaller, these vehicles still play a crucial role in daily passenger and commercial transportation. As a result, the electrification of 2/3Ws presents a promising opportunity to reduce carbon emissions and enhance urban air quality in these regions [137]. In 2023, electric 2/3Ws accounted for 13% of global sales. However, in terms of overall vehicle stock, 2/3Ws remain the most electrified segment of road transport, with approximately 8% being electric [137]. China led electric 2/3W sales that year, with over 30% of total 2/3W sales being electric, though this was a decline from around 50% in 2022, followed by India at 8% and ASEAN countries at 3%. In 2023, the global electric two-wheeler (2W) market declined by 18%, mainly due to supply

chain disruptions caused by China's pandemic restrictions. This was driven by a 25% drop in China, which still dominates global electric 2W sales, accounting for 78% of the market with nearly 6 million units sold, compared to 880 000 in India and 380 000 in ASEAN countries [137].

Despite the global decline, India and some ASEAN countries experienced growth. India, the second-largest electric 2W market, saw a 40% sales increase in 2023, driven by strong policy support like the FAME II subsidy, which ended in March 2024 and was replaced by the short-term Electric Mobility Promotion Scheme (EMPS). Additional policies, such as tax rebates and incentives, have made electric 2Ws more cost-effective compared to ICE models. Figure 1.10 shows the total cost of ownership at 5 years in China and India for 2/3W. Outside of Asia, electric 2/3W adoption remains limited, with Turkey leading non-Asian markets, followed by France, the Netherlands, Italy, and Spain.

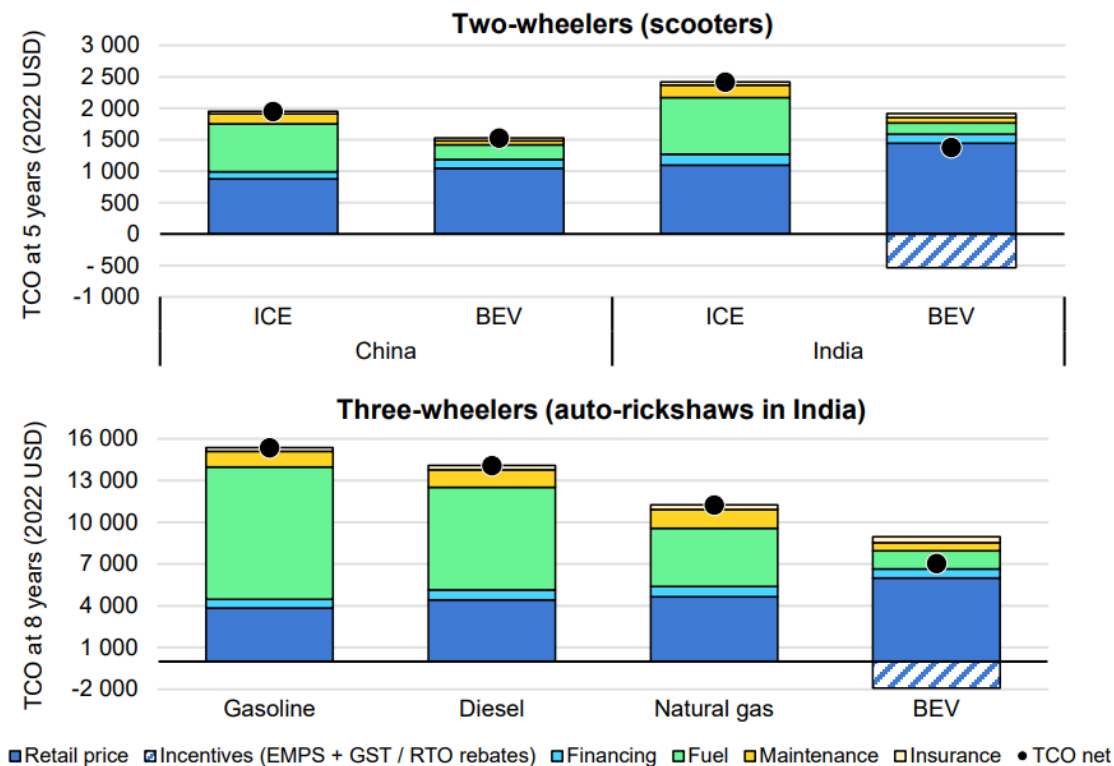


Figure 1.10: Breakdown of the total cost of ownership of two- and three-wheelers in China and India, 2023, from [137].

The total cost of ownership is already lower for BEV motorcycles in China compared to conventional motorcycles, while in India is lower due to the incentives. Furthermore, the retail price is higher for BEV, mainly due to the battery, but the fuel price (electricity) is lower, resulting in a lower total cost over the years.

In 2023, the global three-wheeler (3W) market grew by 13%, reaching 4.5 million sales, with electric 3Ws making up 21% of the total, an increase from 18% in 2022. Nearly 1 million electric 3Ws were sold, marking a 30% year-over-year growth. The market remains highly concentrated, with China and India accounting for over 95% of electric and 80% of conventional 3W sales.

India became the largest market for electric 3Ws in 2023, surpassing China with over 580 000 sales, a 65% increase from 2022, driven by government incentives and lower ownership costs. Meanwhile, China's sales fell by 8% to 320 000 units. Despite efforts to phase out lead-acid batteries in favor of Li-ion technology due to environmental concerns, lead-acid-powered

3Ws remain common in both India and rural China. However, India's 2024 EMPS subsidy scheme aims to accelerate the shift to advanced battery chemistries.

In India, although electric 3Ws cost 55% more upfront than gasoline models, they are over 50% cheaper to own after eight years of use, even without subsidies [137]. Compared to the most cost-effective natural gas-powered 3Ws, electric models reach total cost of ownership (TCO) parity within two years and remain 40% cheaper over eight years. However, subsidies remain crucial in reducing initial costs and ensuring faster TCO breakeven.

1.2.2 Electric motorcycle adoption

Studying the adoption of electric motorcycles is important because they represent a promising solution for mitigating air pollution and combating climate change, especially in urban areas where emissions from internal combustion vehicles are high [4, 30, 69, 144]. In many countries, particularly in Asia and developing nations, motorcycles are the dominant mode of transportation, making the transition to electric alternatives crucial for achieving more sustainable mobility [209, 212].

Despite this, research on adopting electric motorcycles is less developed than on electric cars, especially regarding the psychological and structural factors that influence consumer decisions in these specific contexts [212, 283]. Understanding purchase intentions and barriers to adoption provides valuable information for governments and manufacturers in developing effective policies and targeted marketing strategies that promote electric motorcycles, thus contributing to the environmental and economic sustainability goals.

Furthermore, studying adoption across different geographic contexts is essential, as consumer preferences and success factors can vary significantly from country to country [203]. In remote areas or regions with specific geographical constraints, electric motorcycles can serve as an efficient and sustainable transportation solution where traditional vehicles face challenges [6].

Several key factors influence the intention to purchase electric motorcycles, among them, the most significant include: image, risk, perceived value, perceived usefulness, psychological and attitudinal aspects, economic factors, technological and performance factors, infrastructure and accessibility, and perceived risk. Figure 1.11 shows a proposed framework for investigating electric motorcycle adoption in Indonesia, considering several variables.

A study on the Taiwanese electric motorcycle market highlights that image, perceived risk, perceived value, and perceived usefulness are fundamental determinants of purchase intention [308]. These concepts encompass beliefs about benefits, associated concerns, expected value for money, and the perceived functionality of the product.

A positive attitude toward electric motorcycles is a strong predictor of purchase intention [203]. This attitude is influenced by various factors, including environmental concern, environmental awareness, and ecological values. Emotions associated with the idea of owning an electric motorcycle also play a role. Social influence is identified as a primary driver of the intention to purchase eco-friendly products.

The high initial cost represents a significant barrier to adoption [283]. However, the perception of long-term economic benefits, such as lower operating costs (charging, maintenance) and the perceived value of the motorcycle as a good investment or acceptable price, can positively influence purchase intention. Economic incentive policies, such as purchase subsidies and tax breaks, are highlighted as crucial factors in stimulating adoption [203].

Perceived technical characteristics, such as range, top speed, charging time, and battery lifespan, are important factors [292, 320]. The perceived safety of electric motorcycles is another relevant consideration. Performance improvements can be an effective approach to increasing consumer acceptance [69].

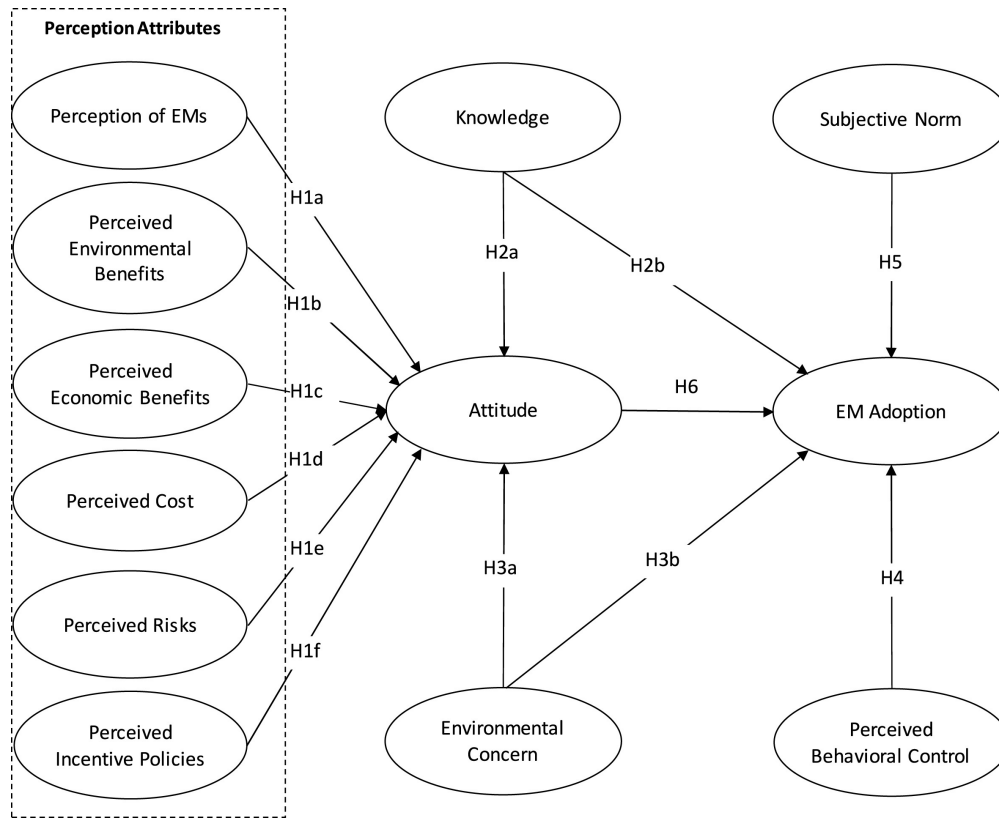


Figure 1.11: Example of research framework for electric motorcycle adoption, from [203].

The availability and accessibility of public and private charging stations are key determinants of purchase intention [320]. Similarly, the presence of easily accessible service centers is important for providing reassurance to potential buyers.

The perception of various types of risk, such as financial risk, performance risk, social risk, and particularly the risk of explosion or fire, can negatively impact purchase intention [320].

The compatibility of electric motorcycles with the lifestyle and values of potential buyers, as well as their observability (the ease with which their advantages can be understood and communicated), are factors that influence attitude and purchase intention.

Although the possibility that two-wheelers can drive toward urban transportation is more sustainable, only e-bikes have immediate market potential due to their immediate added value by the power assisting [303]. While mid-size and large electric two-wheelers have high prices and unclear added value, this prevents the adoption of larger electric two-wheelers.

In summary, the intention to purchase electric motorcycles is a complex and multifaceted phenomenon, influenced by how consumers perceive the image, risks, value, and usefulness of these vehicles, their attitudes and environmental concerns, economic factors, technological performance, infrastructure availability, and compatibility with their lifestyle. Understanding the relative weight of these factors is crucial for developing effective strategies to promote the adoption of electric motorcycles.

2. STATE OF THE ART

2.1 Driving Cycles

2.1.1 Fundamentals of Driving Cycles

Driving cycles (DCs), or speed profiles, or speed schedules are sequences of longitudinal speed values over time. The DCs were created to summarize the vehicle's typical operating conditions and are used in many fields, such as for testing pollution/exhaust emission, vehicle design, engine tuning, and riding range estimation. The DCs should reflect real-world driving conditions and be long enough to represent the driving data well, but not too much to be inefficient during the dynamometer or engine test. For these latter reasons, many DCs were developed, varying the type of vehicle and the driving conditions. Furthermore, motorcycle speed schedules were created for a specific city due to the lack of current DCs representation, like for Hanoi and Edinburgh [258, 281]. When a testing procedure or protocol is added to a given driving cycle, it is called a test cycle. A test cycle may also consider vehicle aspects like cold or hot engine starts, which influence the consumption and pollution emissions.

The speed profiles can be divided into simple-modal and true transient. The former speed profiles are constructed by combining driving modes (acceleration up to, idle for, etc.), like the J10 and the ECE15. In contrast, the latter profiles maintain real-world data and values such as the World Motorcycle Test Cycle (WMTC). Among these two driving cycle types, the transient cycles are currently adopted due to better vehicle driving representation. An extensive summary of the developed motorcycle real-world driving cycle, data acquisition, exhaust emissions analysis, and constructive method can be found in the literature [160, 268]. In table 2.1 are reported the transient cycle with the year, data collection method, constructive method, geographic area, and engine displacement.

Even though many DCs for motorcycles were developed, they were mainly based on low-power vehicles and commuting trips in highly populated urban areas. They were also mainly developed to assess consumption and riding range, and not for performance. In designing high-performance motorcycles, the performance needed in typical riding differs from standard and well-known cycles. Indeed difference in vehicle driving was found among performance levels, with the tendency of having higher speed and steeper acceleration in high-powered cars (power-to-mass > 61 W/kg) [17], suggesting that a more appropriate cycle should be used. Several metrics were developed to describe and compare DCs to each other, such as the duration, average speed, distance traveled, etc. A review of driving cycle metrics grouped by five categories related to physical dimension (time, speed, acceleration, stop, and dynamics)

Table 2.1: Collection of transient motorcycle driving cycles.

Driving cycles	Country	Data collection	Engine displacement	Constructive method
FTP 75 (1973)[158]	USA	onboard measurement	unknown	speed profiles combination and least variance
TMDC (1998)[286]	Taipei	chasing technique	50, 90, 125 cc	least total variance
5 asian city (2003)[43]	Asia	chasing technique	150 cc (chaser motorcycle)	least total variance
WMTC (2004)	Worldwide	onboard measurement	50-1500 cc	speed profile combination and least chi-square value
KHM (2005)[285]	Taiwan	chasing technique	125 cc (chaser motorcycle)	combine driving periods and select the most representative
EDMC (2009) [258]	Scotland	onboard measurement	550 - 1000 cc	run with minimum relative error
CEMDC (2011)[281]	Vietnam	onboard measurement	100 cc	speed profiles combination and least variance
KMDC (2015)[262]	Thailand	chasing technique	113 cc (chaser motorcycle)	speed profiles combination and least variance
Dhanbad DC(2015)[3]	India	onboard measurement	< 200 cc	speed profiles combination and least variance
KKMDC (2019)[156]	Thailand	onboard measurement	1000 W, 108 cc	speed profiles combination and least variance
IMDC(2021)[103]	Iran	onboard measurement	125, 150, 200 cc	speed profiles combination and least variance
Real world eco-drive (2020)[160]	Thailand	onboard measurement	113 cc	speed profiles combination and least variance
E2WDC(2024)[112]	India	chasing technique and onboard measurement	3.3 kW	speed profiles combination and least variance

can be found in [25], which can be used for a quantitative description. Another important tool is the speed acceleration probability distribution (SAPD), which describes the driving data probability to be of a certain speed and acceleration class [133].

An appropriate DC is necessary for the right vehicle design, and it might provide valuable information for correctly sizing the powertrain components. Considering the outstanding performances of which sport motorcycles are typically capable (e.g. max speed over 200 km/h, power to mass ratio > 0.5 kW/kg) the use of the current cycles might fail to provide an accurate estimation of energy consumption and powertrain effort in case of specific applications (e.g. track riding). For example, the World Motorcycle Test Cycle (WMTC) is used to evaluate the L vehicle class emissions [207], and was derived from data collected from vehicles with a considerable power range (from 5kW to 100kW), 518 hours of riding, and 27 224 km traveled.

The duration of the driving cycle is an essential element in assessing its effectiveness. Ideally, a cycle length equal to the original data set would encapsulate all the riding information. However, achieving such lengths results in test cycles impractical for real-world testing and requires extensive computation time for simulations. In contrast, a driving cycle that is too short might not accurately capture fuel consumption [51, 52]. Typically, the lengths of the standard driving cycles range from 600 to 2400 seconds [52, 95].

The analysis of the speed schedule length, referred to as a stable length, after adding more time to the driving cycles, does not significantly affect the fuel consumption, [52]. This latter length depends on traffic and road conditions, indicating that the highway driving cycle needed a shorter length than local and artillery roads [52]. In conclusion, finding the optimal driving cycle length is a trade-off between sufficient consumption accuracy and practical implementation on tests and simulations.

The elevation profiles can significantly impact fuel consumption and, consequently, the accuracy of fuel consumption estimates derived from driving cycles. Road slope, a key aspect of elevation profiles, affects the driving force required by a vehicle and the power delivered by the engine. This is because the road slope directly influences the rolling resistance and aerodynamic resistance that the vehicle must overcome. During uphill driving, higher power is requested due to the increase in potential energy, increasing the consumption up to 28.67% for heavy-duty vehicles in urban context [216]. On the other hand, in downhill driving, the power needed for the propulsion is lower, albeit a net zero potential energy on an entire DC, the influence on consumption will not be null due to the different powertrain operational points, resulting in different efficiency. Although several studies highlighted the significant effects of road slope on vehicle energy demand and consumption [31, 92, 97, 225], the standard approval driving cycles do not consider it at all. The road grade can be collected with different techniques, like the direct measurement with the instrument, calculated from GNSS data [143], and extrapolated from digital elevation models (DEM) [67].

In conclusion, the literature review highlights the importance of designing driving cycles (DCs) that accurately represent real-world driving conditions. These cycles are essential for evaluating vehicle emissions, consumption, and powertrain performance. Optimal DC length is a balance between detail and practicality, with consideration for road slope and elevation impacting fuel consumption. Existing cycles often focus on low-power vehicles and may not adequately address high-performance needs, suggesting the need for more representative cycles for accurate testing and simulation.

2.1.2 Development workflow and constructive methods

The procedure to construct a driving cycle can be summarized in five main steps: route and vehicle selection, data collection, data analysis, using a constructive method to construct

driving cycles, and validation. The schematic workflow for developing a driving cycle is shown in Figure 2.1.

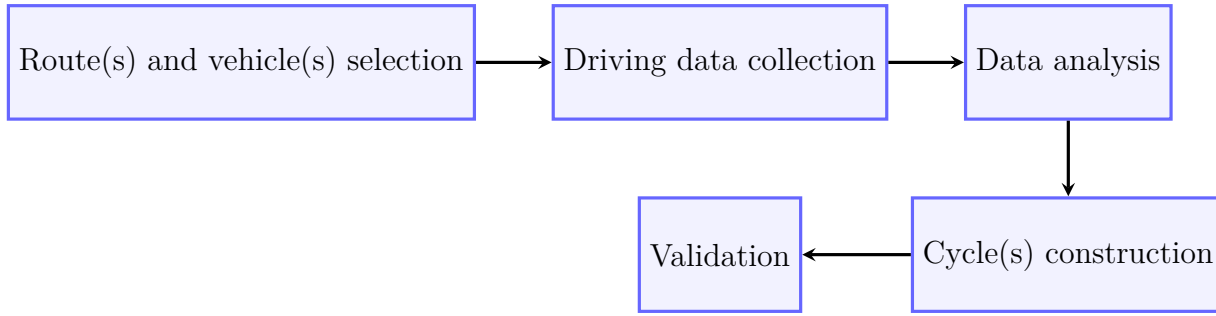


Figure 2.1: Workflow for driving cycle development.

The choice of the route and vehicle defines the set of driving data and should be chosen carefully. After selecting the route, the driving data can be collected using the chase technique or an instrumented ego vehicle [95]. The former method is based on chasing other vehicles with an instrumented car and trying to perform the same behavior as the "prey" vehicle. This approach offers the advantage of gathering data from various drivers using a single instrumented vehicle, although it tracks only a limited number of vehicles. Additionally, this method is restricted to collecting merely the speed and acceleration data of the pursued vehicles. While the chasing method allows for undisturbed driving by the target vehicle, data precision is contingent upon how closely the other vehicle can be tracked. In the end, different runs might be partial due to the inability to follow the whole vehicle driving.

Using instrumented ego vehicles directly collects the driving data, and it is easier to register more than just the speed values. The more instrumented vehicles, the more measurements needed, and so the cost, and they could potentially influence the riding habits of the investigated vehicles.

After the first two phases, the data are analyzed to extract the features or metric parameters, find patterns, and cluster to describe the typical driving condition [16]. Through a constructive driving cycle method, data are converted into one or more driving cycles that summarise the characteristic dataset. As the last step, all the constructed cycles are compared with the reference data via a set of characteristic parameters (CP), called Performance Value (PV) [172]. The cycle with the lowest performance value is chosen among the others, thus, the PV definition is crucial for the final result.

The constructive method is fundamental to building a representative driving cycle that mimics real-world data. Different building methods were developed, which can be collected in four main classes: micro-trip cycle, segment-based, pattern classification, and stochastic modal cycle [54]. A brief description of all these methods will be supplied, and more details can be found in previous works [54, 95, 309].

The first method is based on micro-trips (MT), which are the driving activities between two stops, and it was the most common building method. The micro-trips are extracted from the data and chained together to build a longer trip. The MTs can be added via random selection, quasi-random selection, or searching for specific characteristics. The first method consists of randomly adding a sequence of micro-trips until the desired length is reached and then selecting the best cycle from the other. In the quasi-random method, the initial micro-trip, known as the seed, is chosen entirely at random. The following micro-trips are then randomly selected in a way that enhances the alignment with the samples SAPD [173]. The last adding method is similar to the quasi-random method, but instead of reducing the

error, the micro-trips are selected based on some properties like the class bins and frequency occurrence. The micro-trip itself does not differentiate between modal events like cruising and acceleration, or consider the temporal interdependence of modal activities [173], leading to the possibility of constructing an unrealistic driving cycle. Although different approaches were implemented to expand this method, such as classifying the micro-trip in speed bins, it is best suited to represent only a single type of trip.

The segment-based approach is similar to the micro-trips, with the difference that the segmentation is based on changes in roadway type in addition to stopping. The segments are then chained with some random or best-incremental logic until the desired length is reached. The segments in this method can start at any speed value, thus, particular attention is needed to connect them.

The pattern classification divides the speed into "kinematic sequences" and classifies them into heterogeneous classes. The segments are then added randomly with the probability and time series of the kinematic sequences.

The stochastic modal approach is based on predicting a sequence of driving activities by some stochastic model, like the Markov Chain and Monte Carlo (MCMC). This latter method can model the vehicle driving behavior and be used to build driving cycles based on real-world data [163, 217, 266]. The Markov property of driving cycles was proved on a small time scale, after decomposing the speed profiles on a wavelet series of an approximate signal (low-frequency) and a detail signal (high-frequency) [265]. On a certain road, the speed is stable around a value defined by the road and traffic conditions, and can be approximated via a low-frequency signal. On the other hand, details signals are defined by stochastic traffic flow and driver response. The Markov Chain describes the driving behavior through features extracted from the data that are representative of the driving behavior. The feature choice is essential for a correct and useful representation, and the longitudinal speed and velocity can be used to synthesize speed profiles capturing the fuel consumption [163]. These latter features were used in many other works, but more features can be selected, like the road slope, to construct the DC [266] or added a posteriori [143]. There are no limits to the number of features, and a general multidimensional approach was already applied, adding also a lateral dynamics parameter [80]. Not all the features are important to describe the energy and powertrain efforts, and there are correlations between them. For example, Vehicle Specific Power (VSP), which is the vehicle's tractive power normalized by its mass, has a good correlation with fuel consumption and gas exhaust[95], but it is not a proper cycle metric because it also uses vehicle parameters.

A comparison between the Markov Chain and micro-trips method for light-duty vehicles highlighted the better outperforms of the former method and showed the poor representation of the reference and standard cycles (WLTP, NEDC, UDDS, and FTP-17) [182]. Furthermore, the Transition Probability Matrix (TPM) can store a large amount of data without expanding its dimensions. Indeed, defining a finite number of states and adding more data (i.e. more runs) will change the transition probability values, without increasing the matrix dimension or needing to store all the vehicle runs. In addition, the TPM collects information of the SAPD and speed-time sequence, building a link between them [265].

Finally, a combination of two or more approaches was pursued, like the micro-trip and Markov Chain method. This latter method, for example, was applied to synthesize a driving cycle in Beijing, with micro-trips clustered by bin speed and assigned to a nine-by-nine transition probability matrix [298]. Another study, based on a large number of vehicles (459 passenger cars), divided the trip profiles into micro-trips and then defined driving modes (clustering) and assigned them to a seven-by-seven transition probability matrix [179]. Many other studies applied hybrid techniques for developing driving cycles [182, 228, 238, 295, 312, 315], which are based on data collection, principal coordinates analysis, data clustering, and

utilizing stochastic or genetic algorithms to generate a speed profile.

2.1.3 Metrics for Driving Cycles

Several metrics based on driving cycle parameters were implemented to characterize and describe different driving cycles. These parameters, often referred to as Characteristic Parameters (CPs) [172], are labeled as Performance Values (PVs) [133] when they are employed as a set to regulate or evaluate the synthesized driving cycles. The CPs are variables resulting from speed and time, like the mean speed, the mean positive speed, etc. A DC represents a driving pattern or data by the differences among the characteristic parameters. Among all the studies a discrepancy in the number and the choice of CPs was found [131, 239], finding that the average speed, % idling time, and accelerations standard deviation were the main CPs [239], while another analysis found 16 independent driving factors [78]. On the other hand, different studies for developing motorcycles used many parameters like 10 [103], 11 [285], and 12 [258, 281, 286]. The DC parameters are based on kinematics, excluding any reference to the vehicle, and can be divided into five classes: speed, acceleration, stops, time, and dynamics. The table 2.2 reports the main driving cycle metrics divided by related class. Even if the metrics are derived from driving cycles kinematics, some good linear regression between the parameters and the fuel consumption was obtained [163, 312]. To compare the synthesized driving cycle to the reference data, a subset of all the characteristic parameters is chosen (control parameters), and the relative error between the original data is calculated. Different threshold deviations were applied; in general, values between 5 and 10 % were used. The Speed and Acceleration Probability Distribution (SAPD) is also used to describe driving patterns, classifying the speed and instantaneous acceleration of vehicles in speed-acceleration interval bins. The performance value is obtained as a scalar product of the difference vector and the weights vector [25], expressed as follows:

$$\theta_t = \{x_1, x_2, \dots, x_n\} \quad 2.1$$

$$PV = \left| \frac{\theta_t - \theta_{DC}}{\theta_t} \right| \cdot W \quad 2.2$$

where θ_t is the target statistic set, θ_{DC} is the same statistic set calculated on the driving cycles built, and the x_s are the elements of the statistics set and vary between the metric cycles. When the error is lower than a threshold, the synthesized driving cycle is considered valid. Another method to calculate the error is the Sum Square Difference (SSD) of SAPD, which is the sum of the quadratic error between corresponding speed-acceleration classes. For light vehicles, a good correlation with power, fuel consumption, and exhaust gas was found [145]. The relative positive acceleration (RPA) describes the amount of work needed to increase a mass unitary vehicle speed (kinetic energy), and it is normalized by the total distance as follows:

$$RPA = \frac{\int_0^t a^+(\tau) \cdot v(\tau) d\tau}{\int_0^t v(\tau) d\tau} \quad 2.3$$

where a^+ is the positive acceleration, and v the vehicle speed. This parameter is defined only by the vehicle kinematics and is an indicator of the DC *dynamicty*; it is high when the power demand is high [78]. A speed profile with 0.1 or lower RPA can be considered a *soft* cycle [95]. The RPA metric can be used to compare the harshness of different cycles that have a similar average travel speed [71].

The driving cycles metric ignores any reference to road elevation; for this reason, the characteristic acceleration ($\tilde{a}$) together with the square of the aerodynamic speed (v_{aer}) describes

Table 2.2: Kinematics parameters as metric for driving cycles, from [21, 95, 286].

Group	Symbol	Description	Unit	No.
Speed related	v_{avg}	Average speed	$\frac{km}{h}$	1
	v_{avg}^+	Average running speed	$\frac{km}{h}$	2
	σ_v	Standard deviation of speed	$\frac{km}{h}$	3
	v_{max}	Maximum speed	$\frac{km}{h}$	4
	v_{min}	Minimum speed	$\frac{km}{h}$	5
	IQR_v	speed 75-25th	$\frac{km}{h}$	6
Acceleration related	a_{avg}	Average acceleration	$\frac{m}{s^2}$	7
	a_{avg}^+	Average positive acceleration	$\frac{m}{s^2}$	8
	a_{avg}^-	Average negative acceleration	$\frac{m}{s^2}$	9
	σ_a	Std. of acceleration	$\frac{m}{s^2}$	10
	σ_a^+	Std. of positive acceleration	$\frac{m}{s^2}$	11
	a_{max}	Maximum acceleration	$\frac{m}{s^2}$	12
	a_{min}	Minimum acceleration	$\frac{m}{s^2}$	13
	IQR_a	acceleration 75-25th	$\frac{m}{s^2}$	14
Time related	t	Total time	s	15
	t^+	Running time	s	16
	t^0	Cruising time	s	17
	t_a	Time spent accelerating	s	18
	t_d	Time spent decelerating	s	19
	t_{idle}	Idling time	s	20
	τ	Avg. length of a driving period (from start to stop)	s	21
	-	% of time running	-	22
	-	% of time accelerating	-	23
	-	% of time decelerating	-	24
	-	% of time idling	-	25
	-	% of time cruising	-	26
Stop related	-	Number of stops	-	27
	-	Number of stops per km	$\frac{-}{km}$	28
	-	Number of stops per km	$\frac{-}{km}$	29
	-	Average stop duration	s	30
	-	Average distance between stops	m	31
	-	Max. interm. stop duration	m	32
Dynamics related	RPA	relative positive acceleration	$\frac{m}{s^2}$	33
	PKE	Positive Kinetic Energy	$\frac{m}{s^2}$	34
	RPS	Relative positive speed	-	35
	RRS	Relative real speed	-	36
	RRS	Relative square speed	$\frac{m}{s}$	37
	RPSS	Relative positive square speed	$\frac{m}{s}$	38
	RRSS	Relative real square speed	$\frac{m}{s}$	39
	RCS	Relative cubic speed	$\frac{m^2}{s^2}$	40
	RPCS	Relative positive cubic speed	$\frac{m^2}{s^2}$	41
	RRCS	Relative real cubic speed	$\frac{m^2}{s^2}$	42
	RMSA	Root mean square of acceleration	$\frac{m^2}{s^2}$	43
Distance related	D	Total distance	m	44

the energy demand [147]. The following equations express these two latter parameters:

$$\tilde{a} = \frac{\int_0^t (a(\tau)v(\tau) + g\Delta H)^+ d\tau}{\int_0^t v(\tau) d\tau} \quad 2.4$$

$$v_{aer}^2 = \frac{\int_0^t v(\tau)^3 d\tau}{\int_0^t v(\tau) d\tau} \quad 2.5$$

where ΔH is the elevation increment, a the vehicle acceleration, g the gravitational acceleration, and the superscript $+$ means only positive values are integrated over time. When the road slope is null, the RPA and the characteristics equations are the same parameters: imposing a null elevation on equations 2.4 results in equation 2.3.

In conclusion, Characteristic Parameters (CP) are essential for describing driving patterns and creating driving cycles. Their selection and use significantly affect the representativeness of driving cycles and their ability to replicate the actual energy consumption and emissions of vehicles. Using these parameters is crucial for building representative and reliable driving cycles, and choosing the appropriate parameters and evaluation methods is vital to ensure the accuracy and relevance of the study results.

2.2 Motorcycles market benchmark

Data was collected from electric motorcycle companies to create a database and to have a benchmark for future electric motorcycles. Data are reported in Table 2.3 and are the nominal parameters declared by the companies. In order, the motorcycle mark, model, curb weight, maximum power ($P_{\max}$), torque, battery maximum capacity ($C_{b,\max}$), battery nominal capacity (C_b), battery voltage, and the type of electric machine are reported. For a total of 34 motorcycles, the last one (WATTMAN) was excluded from the analysis because it is not a conventional motorcycle and was built to break the speed record, so 33 motorcycles were analyzed. The motorcycle population ranged from mopeds with small power and battery to racing superbikes built only for riding on tracks or circuits. The information gathered originated from the companies themselves, which meant that there was no means to verify the actual data.

From an analysis of the data in Table 2.3, a linear trend emerges between the maximum battery capacity and the vehicle mass. Figure 2.2 shows the linear fit of the vehicle mass vs. the maximum battery capacity. This latter fit achieved an R^2 of 0,74 and an NRMSE of 7,2%. The vehicle mass can be approximated with a linear function of the maximum battery capacity as follows:

$$m = a_b C_{b,\max} + b_b \quad 2.6$$

Adding also the motor maximum power as a variable to describe the vehicle mass, increased the R^2 value to 0,77 with an NRMSE of 7%, and the result is shown in figure 2.3

The sensitivity analysis reveals the influence of a parameter on the vehicle for energy consumption as defined in [114] as follows:

$$S_p = \lim_{\delta p \rightarrow 0} \frac{[\bar{E}(p + \delta p) - \bar{E}(p)] / \bar{E}(p)}{\delta p / p} = \frac{\partial \bar{E}}{\partial p}(p) \cdot \frac{p}{\bar{E}(p)} \quad 2.7$$

The sensitivity is thus the variation of the function along the parameter p (partial derivative) multiplied by the parameter at the point p and normalized to the function at the point p . For the exponential function e^x , the sensitivity is equal to x , and for the power function x^2 is equal to 2, the growth rate of the geometric series. The same approach can be applied to

Table 2.3: Motorcycles market database

Mark	Model	Weight (kg)	$P_{\max}$ (kW)	Torque (N m)	$C_{b,\max}$ (kW h)	C_b (kW h)	V (V)	EM
Energica	Ego	282	107	200	13.4	11.7	-	HSM
Energica	Ego+ RS	260	126	215	21.5	18.9	-	HSM
Energica	Experia	260	75	115	22.5	19.6	306	PMASynRM
Evoke	6061- XR	320	120	250	15.5	13.6	292	-
Evoke	Urban S	179	20	116.6	10	113.4	72	Brushless DC
Harley David- son	LiveWire	251	120	117	15.5	13.6	-	-
Johammer	J1.150	159	16	-	8.3	-	72	DC syn- chronous
Johammer	J1.200	178	16	-	12.7	-	72	DC syn- chronous
Verge	Ts	249	102	1000	20.2	-	-	-
Zero	SR/S	235	82	190	14.4	12.6	-	PMAC
Zero	SR/S	235	82	190	15.6	13.7	-	PMAC
	pre- mium							
Zero	SR	222	74	166	14.4	12.6	-	-
Zero	DSR	190	52	157	14.4	12.6	-	-
Zero	DSR	210	52	157	18	15.8	-	-
	power tank							
Zero	S	142	34	106	7.2	6.3	-	-
Alrendo	TS bravo	245	20	-	17.4	15	133	PMAC
OttoBike	MCR-S	184	22	361	9.6	-	-	
OttoBike	MCR- M	188	17	279	9.6	-	-	
Ottobuke	MCR- H	9.1	215	4.8	-	-	-	
Lightning	Ls-218	225	150	-	12	-	380	IPM
Lightning	Strike	206	120	250	20	-	-	AC in- duction
	Carbon							
ARC	Vector	230	103	-	16.8	-	399	-
Saroléa	MANX7	217	120	450	14	-	-	Brushless DC
Fuell	Fllow	180	35	750	10	-	400	-
Tarform	-	200	41	-	10	-	-	-
Emuflux	one	169	60	84	9.7	-	100	AC in- duction
Gauss	II	200	110	500	16	-	700	-
Electric	4th	220	170	170	13.5	-	800	-
	super- bike							
Lightfight	V2.0	181	105	162	12	-	365	IPM
Horwin	CR6	134	6.2	260	3.96	-	72	-
Horwin	CR6	140	11	303	3.96	-	72	-
	pro							
DaVinci	DC100	255	100	850	17.7	-	-	-
Vespa	Elettrica	130	4	200	4.2	-	48.1	-
Voxan	Wattman	296	320	5	-	829	-	-

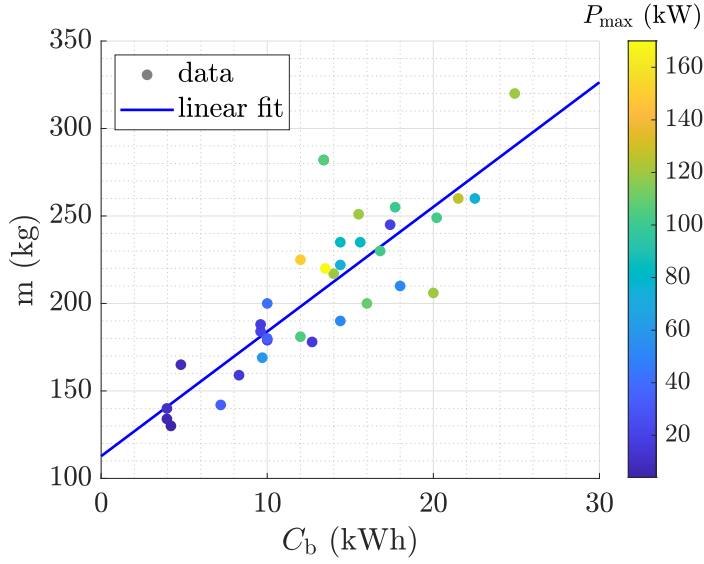


Figure 2.2: Shows the linear trend between the battery capacity and the vehicle mass. Data from Table 2.3 are the plotted dots, and the color indicates the maximum power.

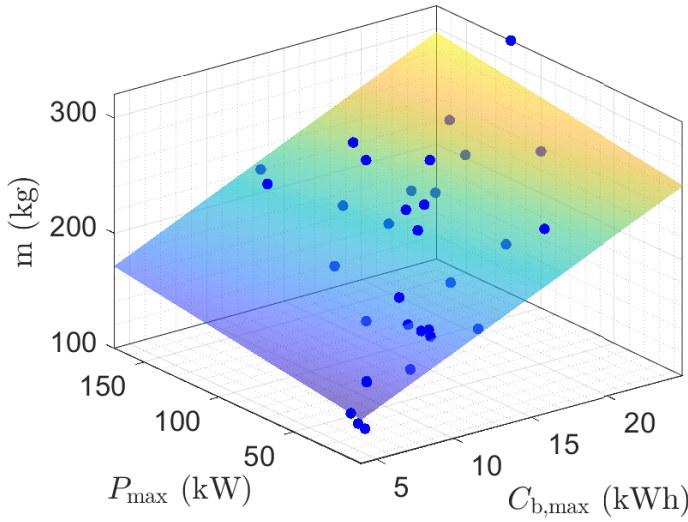


Figure 2.3: Linear fit between the maximum battery capacity ($C_{b,max}$) and the maximum motor power (P_{max}) vs. the vehicle mass (m). Blue dots are the 33 motorcycle values from Table 2.3.

the vehicle mass to investigate battery sensitivity. From equation 2.6, the vehicle mass has a linear relationship with the battery capacity, obtaining as follows:

$$S_b = \frac{\partial m}{\partial C_{b,max}}(C_{b,max}) \cdot \frac{C_{b,max}}{m(C_{b,max})} = a_b \cdot \frac{C_{b,max}}{a_b C_{b,max} + b_b} \quad 2.8$$

where a_b and b_b are the identified parameters from the data reported in table 2.3 between the vehicle mass and the maximum battery capacity in Equation 2.6. Figure 2.4 shows the mass sensitivity to the maximum battery capacity. This model obtained an R^2 of 0,85 and an RMSE of 7.9%, indicating a good correlation with the data.

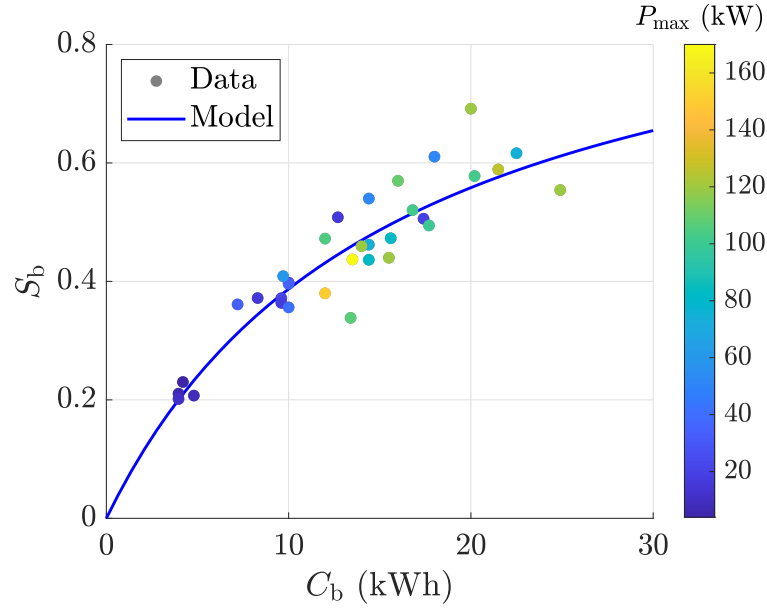


Figure 2.4: Shows the battery sensitivity on vehicle mass. Data from table 2.3 are the plotted dots, and the color indicates the motorcycle's maximum power.

The influence of battery capacity on vehicle mass is more pronounced at higher battery capacities. This is because other components primarily determine the overall mass in vehicles with smaller battery capacities. However, in vehicles with larger battery capacities, the battery represents a significant portion of the total mass. This latter result is clear, taking the limit of the equation 2.8 to infinity as follows:

$$\lim_{C_{b,\max} \rightarrow \infty} a_b \cdot \frac{C_{b,\max}}{a_b C_{b,\max} + b_b} = 1 \quad 2.9$$

Thus, for an infinite battery size, the variation in vehicle mass matches perfectly with the battery size and so mass due to Equation 2.6.

2.3 Energy Consumption and Vehicle Modeling

2.3.1 Energy Flow

The well-to-wheel (WTW) energy conversion encompasses the entire process of converting primary energy sources into vehicle motion. The energy is tracked from the primary energy source to the energy provided to the wheels, including all the energy conversion and transport stages. The energy conversion flows can be divided into the well-to-tank (WTT) and the tank-to-wheel (TTW). The WTT collects all the processes between the *fuel* extraction from the primary source to the vehicle storage. The TTW segment covers all phases of conversion from the vehicle tank or energy source accumulator to the wheels. Despite the WTT and the TTW flows being often cited in many texts [106, 135, 189], a further segmentation is specified with three segmentations. These latter segmentations are well-to-tank, tank-to-vehicle, and vehicle-to-miles (VTM)[114]. This latter segmentation is the energy conversion between the on-board storage system and given by the vehicle dynamics (air drag, tire resistance, etc.) and driving cycles (speed, altitude). The energy flow is shown in Figure 2.5. The cradle-to-grave valuates also the energy needed to produce the vehicle to its end of life [106]. The well-to-tank phase for electric vehicles examines the environmental impact associated with the production and distribution of the electricity used to charge their batteries before the energy

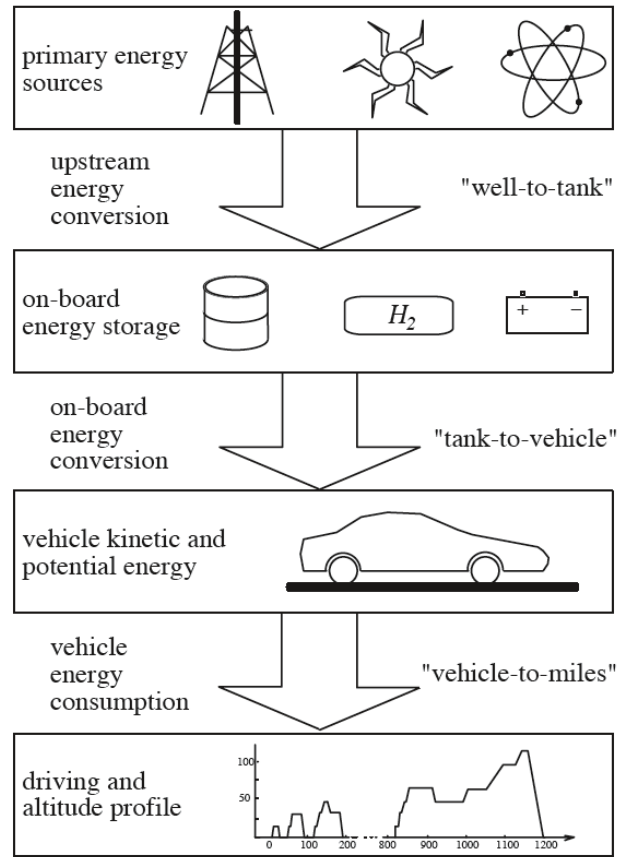


Figure 2.5: The main elements of the energy conversion scheme, from [114].

is used for propulsion. This process includes the emissions and energy consumption related to the extraction of raw materials, the conversion of primary energy into electricity, and the losses during transportation and distribution on the electric grid. Scientific studies indicate that although electric vehicles do not produce tailpipe emissions, their overall environmental impact is strongly influenced by the energy mix used [100, 168]. In regions where electricity production relies heavily on fossil fuels, well-to-tank emissions tend to be higher, whereas a greater share of renewable energy sources can significantly reduce these emissions.

Although electric vehicles eliminate tailpipe emissions, significant environmental burdens remain in the upstream stages, particularly in battery production and the electricity generation mix. The upstream emissions may substantially influence the overall ecological performance of electric powertrains [118], and accounting for the entire supply chain is crucial when assessing vehicle impacts [74]. A comparison in Istanbul with cars shows a reduction in emissions of 60% for EVs compared to ICEs on the well-to-wheels process [221]. In the case of electric motorcycles, following the UN ECE Regulation No. 40 speed profile, it was found an 87% energy consumption reduction, a 53.8% lower CO_2 emission and saved cost by 82 % compared to hybrid motorcycles running only ICE mode; while hybrid motorcycles did not performed significantly better than the only ICE models [321].

The transition to electric vehicles offers practical means to decrease the use of non-renewable primary energy and minimize greenhouse gas emissions. These benefits are particularly significant in city driving, characterized by lower average speeds, which constitute the bulk of daily trips, while the advantages are less pronounced on highways and longer routes [327]. Enhancing well-to-tank efficiency is not related to the automotive industry but can be achieved by optimizing each portion of upstream processes or replacing primary energy sources with more energy-efficient alternatives to fossil fuels[189]. An analysis of real-world

data from 400 commercial vehicles found as more cost-effective the solution to increase fast-charging infrastructure than increasing the battery size; preferring the second solution for high BEV fleet shares [94].

In summary, electric vehicles reduce energy consumption, and the upstream process is vital for reducing it, particularly in electric vehicles where the electricity mix is a significant factor. These processes occur independently of the vehicle itself. This thesis focused on designing appropriately sized electric powertrains based on driving cycles, and consequently, these upstream processes were not examined within this study.

2.3.2 Vehicle modeling and Energy Consumption

Vehicle dynamics modeling is essential for estimating fuel consumption and energy efficiency. Various simulation tools and techniques are available for this purpose, each offering different levels of complexity and accuracy. Simulation can save time and costs in predicting energy usage and provide in-depth results on vehicle performance [189]. Objectives of modeling and simulation include: predicting fuel consumption and emissions, providing component parameters like the battery size, saving time and costs in forecasting solutions, and cost-benefit analyses [135].

The main factors that influence energy consumption are: speed profiles, slope gradients, auxiliary systems, and traffic [61]. The models can be divided by the energy flow direction: forward vehicle model (FVM) or cause-effect and backward vehicle model (BVM), or effect-cause differentiated by how the traction forces are estimated [198]. The first approach starts from the already known powertrain characteristics and computes traction forces requested by the driver and generated by the powertrain unit to estimate vehicle kinematics through the vehicle modelization; the other starts from already known kinematic quantities and computes traction forces required from the powertrain unit to be generated, estimating the powertrain performance. The forward method demands a significantly high runtime because of intricate feedback loops and control algorithms, but it enables the integration of rapid prototyping and hardware-in-the-loop capabilities. On the other hand, the backward method takes a more black-box approach, modeling each drivetrain component independently. This method is generally more modular, allowing for swift software development and considerably faster simulation runtimes [289]. The forward and backward methods, with the direction of energy flow and calculation, are shown in Figure 2.6.

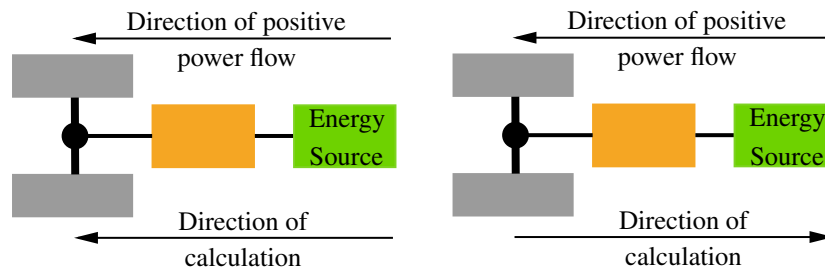


Figure 2.6: On the left is shown the forward method or cause-effect, and on the right the backward method or effect-cause. This latter method neglects the driver's behavior, while the former uses a speed controller (like PID) for simulating the driver.

Through the vehicle model, the vehicle kinematic (speed profile) is mapped to the vehicle dynamics (forces, power, etc.). The modeling process typically includes the following key aspects: longitudinal dynamics, lateral dynamics, and vertical dynamics. The longitudinal dynamics involves modeling the forces acting along the direction of motion, and it is used to estimate the power and energy vehicle demand. Lateral dynamics focuses on vehicle

handling and stability, modeling forces during cornering, and steering control. These latter dynamics usually make a contribution to energy consumption that is negligible compared to longitudinal for motorcycles, as shown in section 4.4.4. An analysis of electric motorcycle cornering was investigated and found a significant effect on energy consumption, although not specifying the curve radius and the lateral acceleration [82]. The vertical dynamics include the modeling of suspension systems, road irregularities, and ride comfort. A detailed vertical dynamics model helps optimize the suspension setup for improved safety and comfort. Mathematical models for electric vehicles span from the single degree of freedom (single point mass) to complex multi-body models crucial for handling maneuvers [253]. These latter models consider kinematics constraints, cross-coupling effects between sub-components, as well as non-geometrical linearity. The fundamentals of vehicle dynamics and performance established for conventional vehicles are still valid for electric vehicles [98]. Complex multi-body allows simulation of reasonably general motions and stability, modal and response computations for small perturbations from any trim condition [263]. Vehicle parameters like the mass, tire radius, and cross-sectional area influence the consumption. A study on an electric moped investigated the electric motorcycle mass, driver mass, wheel radius, frontal area, and transmission ratio variation as influencing the consumption [125]. Altering the motorcycle's weight from 60 kg to 100 kg resulted in a 5.9% reduction in riding range and a 0.11% rise in electricity consumption. Meanwhile, expanding the radius by 19.5% led to an 11.2% improvement in riding range [125].

Including the load transfer, the normal force acting on the axles will change during the ride, which results in changes in the rolling resistance that for cars can be up to a 7% difference in relative power consumption due to the tire deformation [57]. The longitudinal, lateral, and vertical dynamics are coupled, but mainly the longitudinal dynamic is used to predict the vehicle energy consumption.

The tire-road friction coefficient changes on cornering due to the load transfer, and implementing a control method on torque distribution allows a 29.1% increase in energy efficiency, avoiding tire force saturation [167]. The electric vehicle allows torque vectoring control via independent wheel motors. Allocating the right amount of torque for each wheel makes it possible to recover more energy, leading to an energy consumption reduction of around 10% [153], 20.98% [129], 8.7% [154] for many typical driving conditions. A study on sensor-less torque repartition strategy between the front and rear wheels on motorcycles found an increment of efficiency of 15% and 8% than the just rear wheel driven motorcycles for the WMTC and their non-standard speed profile, respectively [166]. A 13-d.o.f. multi-body motorcycle model, including the effects of suspension, aerodynamics, and gyroscopic bodies, was used to investigate the impact of torque distribution on energy consumption during steady-state straight line and cornering situations in terms of mechanical energy [108]. This latter study found that running on a straight line with the optimal torque repartition, the power reduction was 1.6%, and 0.2% on cornering with a constant radius. The possibility of optimal torque management allows recovery of more energy during braking and reduces cornering resistance on sharp cornering for cars [245].

Once the mechanical energy required is known, given a vehicle and a speed profile, the efficiency analysis can be performed with three approaches: average operation point, quasi-static, and dynamic [114]. The first approach lumps all the operating points into one single point, representing the average, and computing the fuel consumption at that regime. This latter approach can be used as a preliminary approximation of a simple powertrain. The second approach considers small time steps for which the speed, acceleration, and eventually the road angle are constant over time. The second approach is equal to applying the average single points to many time intervals. Usually, the time intervals are all equal with a length

of 1 second, and for short time intervals, the consumptions are accurate [114]. The third method described the system mathematically using a set of differential equations, partial equations, and algebraic parts. This approach allows capturing the dynamic effects that might be significant for consumption, increasing the system complexity. The data-driven analysis approach is an alternative to the vehicle model approach to estimate consumption. This latter approach is based on algorithms tuned on data for predicting the energy consumption [61]. The computational performances of the model are related to the level of detail considered throughout the modeling process. The model's computational performance depends on its level of detail.

A simplified vehicle model enables fast and accurate energy consumption estimates with minimal computation but sacrifices dynamic simulation quality. In contrast, a detailed model improves vehicle dynamics accuracy at a higher computational cost. This approach allows for testing multiple design variants and optimizing numerical models, reducing reliance on costly physical prototypes. It also supports virtual and augmented reality applications, control algorithm development, and energy management system (EMS) testing. However, a key limitation is the models lack of interaction with the external environment.

The data-driven method is effective when abundant data is available at the start of the analysis. It begins with clustering data, which can include driving cycles, behaviors, traffic patterns, and real-world habits collected through continuous monitoring [11, 130, 293]. Unlike the vehicle model-driven approach, it operates without a vehicle model, relying instead on machine learning for correlation analysis [197]. Various algorithms and statistical evaluations refine the raw dataset into a reliable starting point. The core of this method lies in data processing, where key differences from model-driven approaches emerge.

The hybrid approach combines data-driven and vehicle model-driven methods to enhance simulation detail. Data-driven techniques preprocess and refine datasets, creating scenarios that represent different behaviors or conditions [117]. The vehicle model then simulates these scenarios [174, 304], enabling result comparison and assessment. While this method improves accuracy, it is time-consuming and computationally intensive due to the large data processing. A key advantage is its ability to extract real-world patterns and validate them through numerical analysis, optimizing energy consumption and management in EVs. Finally, statistical refinement further improves results.

A comparative analysis of a nonlinear physical model, a linear state-space model, and a neural network model across two distinct car models reveals that the data-driven approach outperformed the physical model for both vehicles. This indicates that the linear data-driven model strikes an optimal balance between accuracy and simplicity [140]. On the other hand, building complex models requires the right data.

Electric vehicles can harvest energy via regenerative braking and regenerative suspensions to reduce energy waste and increase efficiency. Other energy harvesting could be by on-board solar panels, and micro wind turbines to extend the range of the vehicle. This latter solution shows an increment of 16, 11, and 2 km of range for the FTP, NEDC, and RTS driving cycles, respectively [68]. While a solar panel installed on a vehicle's roof should primarily be viewed as a secondary energy source, it still offers valuable energy benefits by lowering both grid-charging expenses and the vehicle's carbon emissions during operation [26]. For several years, research has been conducted on harvesting energy within vehicle suspensions, starting from the mid-90s [1]. Regenerative suspension instead of absorbs vibrations and dissipates energy in heat, converting the vibration energy into electricity. Field tests using prototype models reveal that the power generated from suspension harvesting is 100 - 400 W for cars, and improves by 3% in lowering fuel efficiency [1]. Another study reports that the energy consumption is reduced by approximately 2.8% and the RMS value for

vehicle body acceleration is reduced by more than 31% using active suspension system with energy recovery instead of a passive damper [230]. Although the advantages of regenerative suspension may seem limited, energy harvesting solutions can potentially contribute to lower the overall energy use of semi-active or fully-active suspension systems [142].

The recuperation of energy during braking considerably affects the driving range of electric vehicles. In typical city traffic, the peak braking power generally remains within the limits of what the regenerative braking system (RBS) can handle [99]. RBS allows an increment of the riding range from 8% to 25% [46]. On the other hand, the energy recovered depends on the state of charge (SoC) of the battery, and high charging current using regenerative braking deteriorates battery life [20] but also lowers the battery degradation when partially refilled via short recharging periods during braking moments [148]. EVs particularly benefit from a high level of regeneration, but only when low recharging currents are used [149]. Indeed, high regeneration rates require batteries with a higher admissible charge current or ultracapacitors on vehicles [40]. During vehicle coasting, due to forces resistance and regenerative braking, at speeds between 0-60 mph, motorcycles can reach deceleration between 0.10 - 0.33 g with the only rear wheel driven [231]. In the case of racing motorcycles, a study on 25 circuits found that via RBS around 7.88% to 14% of energy can be recovered, with an average of 11.11%, increasing the distance traveled by 8.8% on average [241]. In another study on an electric superbike (max power 160 kW), the regenerative braking improved the range by 14% and the riding ranges varied from 30 km on tracks to 112 km on road [162]. In racing, the energy recoverable is linearly correlated to the average circuit speed; the lower the speed, the higher the regenerative ratio [241].

In conclusion, to evaluate new powertrain solutions, a vehicle-model approach is used, and the vehicle dynamics models will be detailed in Chapter 4. This latter model is crucial for the accurate estimation of energy consumption and efficiency to assess the best design. The vehicle model represents a quasistatic back-forward approach, chosen for its simplicity while still possessing the ability to accurately predict consumption, as derived from earlier analyses. Vehicle handling can be neglected to estimate energy consumption, so focusing on a simpler model allows for a reduction in the complexity and the calculation time. Furthermore, the principles and benefits of regenerative braking, including its role in energy harvesting and improving efficiency in electric vehicles, will be discussed in further detail in Chapter 6 both on flat and on uphill roads.

2.4 Energy sources

The energy sources for electric vehicles (EVs) represent a crucial aspect of their functionality and widespread adoption. Unlike conventional vehicles, EVs are powered by electric motors that draw energy from various sources. These primarily include energy storage systems such as batteries, ultracapacitors, and fuel cells, which can be recharged through the electrical grid, often supplied by power plants or renewable resources. Additionally, some EVs integrate onboard energy generation units or energy recovery to extend their range. The diversity and evolution of these energy sources are essential for improving the efficiency, range, and sustainability of electric vehicles.

2.4.1 Flywheel

A flywheel for electric vehicles is a mechanical energy storage device that stores kinetic energy in a high-speed rotating rotor [135]. In electric vehicles, the flywheel can be used as an auxiliary energy source to improve efficiency, provide additional power during acceleration,

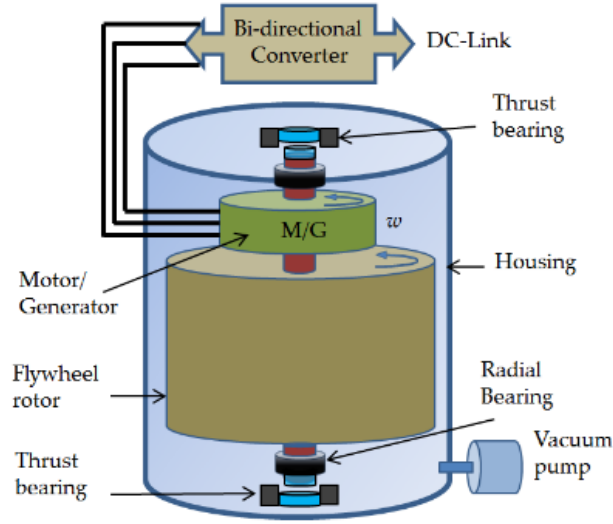


Figure 2.7: Example of flywheel system from [12].

or quickly store energy recovered from regenerative braking [60, 77, 276]. It is often used with batteries to optimize the overall performance of the electric propulsion system [60, 276]. The basic principles of a flywheel are based on storing kinetic energy through the rotation of a mass. An example of the flywheel system is shown in Figure 2.7. The amount of stored energy (E) is directly proportional to the rotor's moment of inertia and the square of its angular velocity as follows:

$$E = \frac{1}{2} I \omega^2 \quad 2.10$$

where I is the spin flywheel moment of inertia, and ω is its angular velocity. For a solid disk, the moment of inertia is expressed as:

$$I = \frac{1}{2} m r^2 \quad 2.11$$

where m is the rotor mass, and r is the outer radius. To store or utilize electrical energy, the flywheel is typically coupled with an electrical machine (motor/generator) that converts electrical energy into kinetic energy during charging (the motor accelerates the rotor) and kinetic energy into electrical energy during discharging (the generator slows down the rotor) [13, 76, 276]. In electric vehicles, the flywheel uses this capability to rapidly store energy recovered from regenerative braking and provide additional power during acceleration, helping stabilize power delivery and potentially protecting the main battery from current peaks [60, 276]. Compared to other storage technologies, flywheels offer a high number of charge/discharge cycles, high power density, long operational life, reduced environmental impact, and the ability to store energy levels in megajoules (MJ) without an upper limit when configured in banks [12]. They excel particularly in high-power applications with a specific power up to 5.5 kW/kg, positioning themselves closer in functionality to supercapacitors rather than batteries [122]. The idea of combining a high-power flywheel with a high-energy battery aims to overcome the limitations of batteries alone in terms of peak power delivery and increasing their lifespan by protecting them from high currents [60]. There are three main types of flywheels: electric, mechanical, and electromechanical. The former flywheel employs a high-speed integrated motor to convert kinetic energy into electrical energy and vice versa. The mechanical flywheel accumulates energy directly from the transmission and can not convert energy, it shows the advantages of high efficiency and compact structure. The mechanical flywheel device is only applied to fuel vehicles. The electromechanical can

achieve input and output control of both electric and kinetic energy. Electric energy control is achieved by a speed control motor, while kinetic energy control is realized by the flywheel. So electromechanical flywheel device shows greater freedom for design, control, and application. To maximize stored energy, the electric flywheel should operate at very high speeds (up to 40 000 r.min⁻¹) and require sophisticated and costly components, such as magnetic bearings, hybrid ceramic ball bearings, and vacuum systems to ensure efficient and safe operation [276]. Furthermore, under certain driving conditions, the energy losses of the electric flywheel caused by the frequent operation of the control motor at high speed and low torque (with a low average efficiency of 75.9%) can outweigh the benefits gained from improved battery efficiency, leading to an increase in the system's net energy loss [276].

The top speed a flywheel can spin at is dictated by its rotor's material strength, known as tensile strength (σ) [12]. The tensile strength for a thin rotating disk is given by:

$$\sigma_{\max} = \rho r^2 \omega^2 \quad 2.12$$

where ρ is the material density. To evaluate the effects of the geometric rotor, the shape factor for the specific energy and energy density

$$\frac{E}{m} = K \frac{\sigma_{\max}}{\rho} \quad 2.13a$$

$$\frac{E}{V} = K \sigma_{\max} \quad 2.13b$$

where K is dependent on the rotor's shape, and V is the rotor volume. Equations 2.13a and 2.13b indicates the specific energy ($\frac{J}{kg}$) and the energy density ($\frac{J}{m^3}$) respectively. Noteworthy that the specific energy and density energy are independent of the rotor speed. Shape coefficients range from 0.5 for a thin ring to 1 for the Laval disk [310]. Energy density ranges from 28 Whkg⁻¹ for the aluminum to 53 418 Whkg⁻¹ for single wall carbon nanotube [123]. According to Equation 2.10, the stored energy of a flywheel can be optimized by increasing either the spinning speed (ω) or the moment of inertia (I). There are two options for Flywheel Energy Storage Systems (FESS): low speed (up to 10 000 rpm) and high speed (up to 100 000 rpm). Low-speed flywheels use heavier metallic materials and can employ mechanical or magnetic bearings, while high-speed flywheels often require lighter composite materials and magnetic bearings. High-speed flywheels can be significantly more expensive.

Flywheel technology represents a promising solution for improving the efficiency and performance of electric vehicles, especially in hybrid configurations with batteries. The different types of flywheels, such as electric and electromechanical, offer distinct approaches with specific advantages and disadvantages in terms of efficiency, cost, and control. Research and development in this field continue, to overcome technical and cost challenges to enable wider adoption of this technology in the automotive sector.

2.4.1.1 Ultracapacitor

Ultracapacitors (UC), also known as supercapacitors (SC) or electrochemical double layer capacitors (EDLCs), are electrochemical energy storage devices with characteristics that fall between conventional capacitors and batteries [63, 233]. They are especially well fit for applications with long life and high power but low energy. Ultracapacitors have a structure similar to conventional capacitors but offer significantly higher capacitance, approximately 20 times greater [279]. Energy storage in EDLCs occurs through the formation of an electric double layer (EDL) at the interface between the electrode and the electrolyte, a purely electrostatic phenomenon [42, 73]. Figure 2.8 illustrates a schematic of a double-layer ultracapacitor.

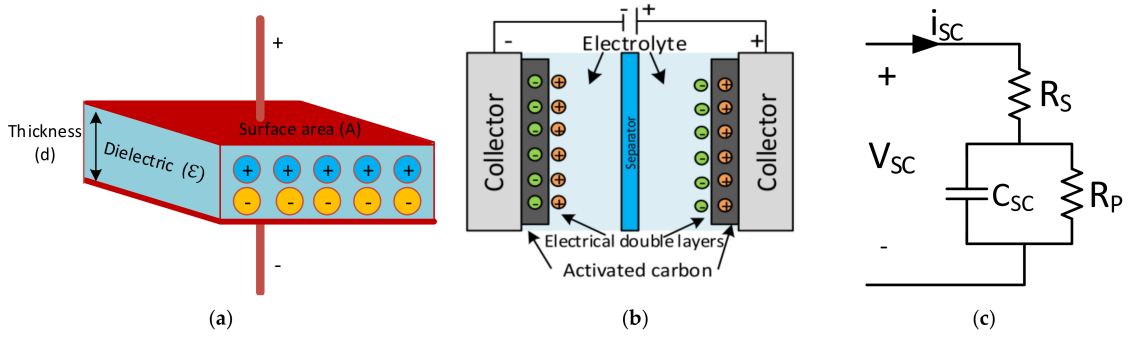


Figure 2.8: a) Structure of electrostatic capacitor, b) structure of SC, c) equivalent circuit model of SC, from [255].

Ultracapacitors are characterized by high specific power (the ability to deliver and absorb large amounts of power rapidly) and a higher energy density compared to conventional capacitors, although lower than that of batteries [63, 233, 297]. Despite UCs having many features in common with batteries, the basic difference is that a capacitor is an electrical energy storage device, while a battery is a chemical energy storage device. In capacitors, energy is stored via charge separation in an electrostatic field between electrodes. Ions in the electrolyte move towards oppositely charged electrodes, creating a double layer at the interface with the electrodes' micro-porous surfaces, allowing for rapid charge/discharge due to the absence of chemical reactions. A capacitor is similar to a battery cell, consisting of two electrodes, a separator, and an electrolyte. Unlike batteries, capacitors use micro-porous materials for electrodes to increase surface area. The separator must allow ion movement in the electrolyte, which is typically an organic, aqueous, or ionic liquid. Other key features include a long operational lifespan (many more charge and discharge cycles than batteries) [233, 279, 297], extremely fast charge and discharge times [63], a wide operating temperature range, and minimal or no maintenance [279]. There are three types of ultracapacitors: EDLCs, pseudocapacitors, and hybrid capacitors (or asymmetric). Ultracapacitors store energy electrostatically through charge separation in the electric double layer that forms at the interface between the electrode (usually carbon-based) and the electrolyte, via a non-faradic process [24, 76]. Pseudocapacitors store energy through faradic redox reactions occurring on the surface of electrode materials (such as metal oxides or conductive polymers), offering higher energy density compared to EDLCs but potentially lower power density and cycle life [24, 255]. Hybrid (or asymmetric) capacitors combine the storage mechanisms of EDLCs and pseudocapacitors, typically using one electrode with EDLC behavior and the other with pseudocapacitive behavior to balance high power with increased energy storage [24, 36, 76]. The energy density of EDLCs is generally the lowest among different UC technologies (5-7 Wh/kg), while pseudo-capacitors and hybrid capacitors can achieve similar energy densities (10-15 Wh/kg). The power density is similar across all three types, around 1000-2000 kW/kg for pulses with 95% efficiency, with EDLCs exhibiting slightly higher power density [279]. The UC lifetime can reach 40 years, which is the longest among all energy storage systems.

The fundamental concept of UCs is based on capacitance (C), the ability to store electric charge, and is described by the following equation:

$$C = \frac{A\epsilon_0\epsilon_r}{d} \quad 2.14$$

where A is the surface area of the plates, ϵ_0 is the permittivity of air, ϵ_r is the relative permittivity of the dielectric material, and d is the distance between the plates. The amount

of energy that can be stored is given by:

$$E = \frac{1}{2}CV^2 \quad 2.15$$

where E is the energy, and V is the cell voltage. Thus, the amount of stored energy depends on the electrode surface size, the distance between them, the material properties, and the cell voltage. To increase the energy density of a capacitor it can be increased the capacitance or the cell voltage. The cell voltage can be increased by selecting a different type of electrolyte or by leveraging the benefits of asymmetric capacitors, which incorporate both faradic and non-faradic processes.

The modeling of ultracapacitors can be approached with different levels of complexity to capture their behavior. Equivalent circuit models (ECMs) are widely used in practice due to their simplicity, approximating input-output behavior with circuit structures. Among these, the classic model consists of an equivalent capacitor (C_p), an internal series resistance (R_s), and a self-discharge resistance (R_p) [297, 324]. More complex models, such as the multi-stage ladder model and the dynamic model, offer greater accuracy at the cost of higher computational complexity [324]. There are also physics-based models (PBMs) [297], which provide higher internal accuracy but are difficult to parameterize. Modeling can also account for component non-idealities, especially in energy storage systems with DC/DC converters [223].

The sizing of an ultracapacitor depends on application requirements, such as the desired discharge power, expected backup duration, and the minimum voltage limit [222]. A common design choice is to set the minimum discharge limit at 50% of the nominal voltage [222]. Sizing involves determining the required capacitance and nominal voltage (achieved by connecting cells in series and parallel). Key factors include peak voltage, maximum allowable discharge, peak current, and individual cell characteristics (capacitance, voltage) [63]. Sizing also affects the selection and evaluation of the power rating of the interface electronics. For high-voltage applications, multiple cells must be connected in series, requiring voltage balancing circuits to prevent the overcharging of individual cells due to capacity variations [63].

Due to their characteristics, ultracapacitors are ideal for applications requiring high power for short durations, such as starting, acceleration, regenerative braking in vehicles [19, 297], and reducing the load on primary power systems during sudden power fluctuations [297]. A study on hybrid battery-UC design found an additional 30 km of driving range than the only battery configuration for a passenger car [19].

2.4.2 Fuel Cell

A fuel cell is an electrochemical device that converts the chemical energy of a fuel (typically hydrogen) and an oxidant (often oxygen from the air) directly into electrical energy through a reaction that generates water as the primary byproduct [267]. Unlike batteries, which store chemical energy, fuel cells generate electricity as long as fuel is supplied. This process is highly efficient (highest efficiency from 40% to 85%) and environmentally friendly, producing little to no harmful emissions, unlike traditional combustion engines that burn fossil fuels.

A fuel cell consists of two electrodes: an anode (negative electrode) and a cathode (positive electrode), separated by an electrolyte membrane. The fuel, such as hydrogen, is supplied to the anode, where it dissociates into protons and electrons. The protons pass through the electrolyte membrane to the cathode, while the electrons travel through an external circuit,

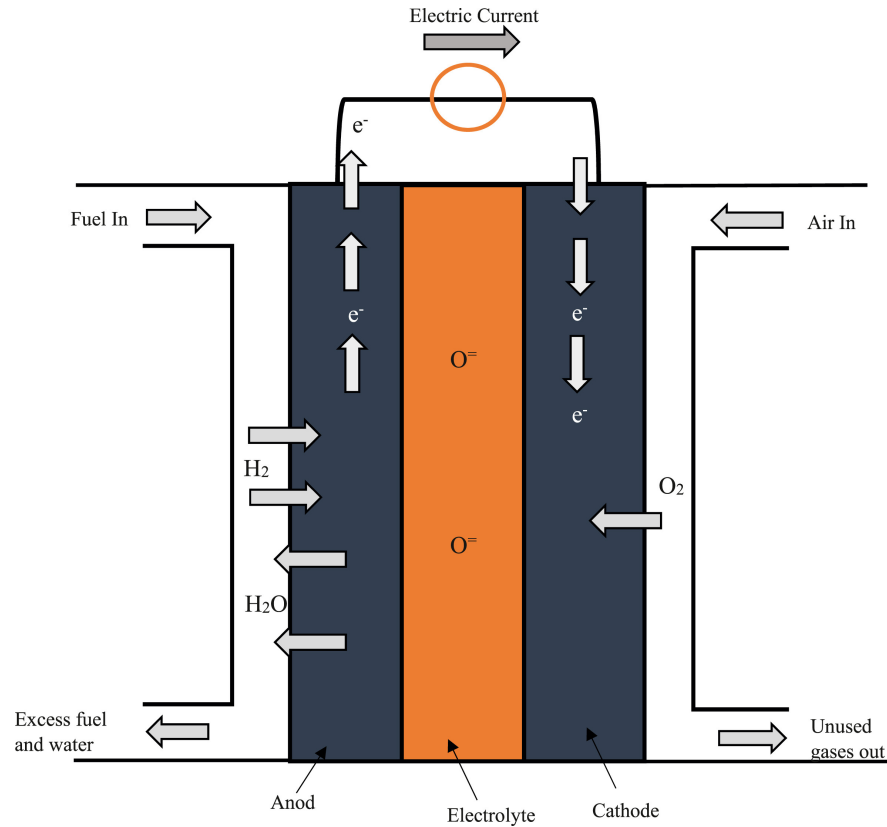


Figure 2.9: Schematic representation of a fuel cell from [267].

generating an electric current. At the cathode, the protons, electrons, and oxygen combine to form water vapor. Figure 2.9 shows a schematic of a fuel cell.

Fuel cell electric vehicles (FCEVs) are considered a complementary technology to battery electric vehicles (BEVs) in achieving zero-emission mobility, particularly in scenarios requiring longer range, where batteries may be insufficient due to size and long charging times [299]. In FCEVs, fuel cells generate the electricity needed to power the electric motor by combining onboard-stored hydrogen with oxygen from the air [76]. A typical FCEV system includes a fuel cell stack, hydrogen tanks, a high-capacity battery (for energy recovery during braking and peak power demands), and auxiliary components such as air compressors, humidifiers, and electronic controls [205]. The fuel cell stack is the core of the system where electrochemical conversion occurs. Hydrogen tanks store onboard hydrogen. Safe hydrogen management and storage remain major challenges. The battery is used in hybrid configurations (FCHEV) to store energy recovered during regenerative braking and to provide extra power during peak demands. DC-DC converters and inverters manage power distribution between the fuel cell, battery, and electric motor. The thermal management system maintains the optimal operating temperature of the fuel cells. The air supply system delivers oxygen to the cathode, and finally, the hydrogen management system regulates hydrogen flow to the anode. Among various fuel cell types (alkaline, molten carbonate, phosphoric acid, solid oxide, and direct methanol), proton exchange membrane fuel cells (PEMFCs) are considered the most suitable for vehicle applications due to their low operating temperature, high power density, and fast startup capability [81, 252]. However, solid oxide fuel cells (SOFCs) are also being researched for electric vehicle applications [81].

The benefits of the fuel cell are zero tailpipe emissions (the only byproduct is water), fast refueling (about 3-5 minutes, similar to refueling a conventional fuel tank) [205], longer range, and lower sensitivity to ambient temperature. Fast refueling is a significant advantage

over BEV charging times, which often take several hours. The longer range is due to hydrogens higher energy density compared to lithium-ion batteries. A fuel cell system typically offers 0.69-1.5 kWh/kg, whereas lithium-ion batteries provide 0.14-0.24 kWh/kg [205]. Thus, FCEVs can achieve greater range than BEVs with similar weight batteries. Despite their advantages, FCEVs face several challenges high costs, availability of hydrogen refueling infrastructure, hydrogen production and storage, and public awareness. The high costs come from the fuel cell and hydrogen tank, while nowadays the availability of hydrogen refueling stations is limited. Finally, making hydrogen production, transportation, and storage more cost-effective and sustainable is essential. Currently, most hydrogen is produced from fossil fuels, though greener methods such as renewable-powered water electrolysis are being developed [44]. Due to hydrogens low volumetric density, onboard storage remains a technical challenge [204]. Many FCEVs are designed as hybrid vehicles (FCHEVs), combining a fuel cell with a battery and/or ultracapacitors [204]. This hybridization helps overcome the limitations of individual energy sources, improving efficiency, performance, and energy management. The battery or ultracapacitor can provide additional power during acceleration and store energy recovered during braking, while the fuel cell ensures a continuous energy supply to keep the battery charged and power the motor [299]. A prototype hydrogen fuel cell-powered motorcycle, named Pios, was developed for the South African Solar Challenge in 2008 [300]. The latter motorcycle is shown in Figure 2.10. Pios was equipped with a 9 kW hub motor (peak power), a buffer lithium battery of 51.8 V and 20 Ah capacity, a 14.5 Farad ultracapacitor for peak power storage, 1.3 kg of hydrogen storage at 350 bar, and a 7 kW fuel cell for continuous power. These latter features result in a 300 km riding range cruising at an average speed of 75 kph, and a curb mass of 298 kg.



Figure 2.10: Pios Fuel Cell Motorcycle prototype frame [300]

The adoption of fuel cells in motorcycles presents specific challenges: space and weight, hydrogen storage, costs, and infrastructure. Integrating the components of a fuel cell system (stack, hydrogen tank, etc.) into a motorcycle, where space and weight are extremely limited, is a significant engineering challenge. Safely and efficiently storing a sufficient amount of

hydrogen on board a motorcycle is complex due to hydrogens low volumetric density. As with cars, fuel cell technology costs need to be reduced to make hydrogen-powered motorcycles competitive.

Fuel cells offer a promising, clean, and efficient alternative to internal combustion engines for electric vehicles, with significant advantages in emissions, range, and refueling time. Although there are still challenges to overcome regarding cost, infrastructure, and durability, ongoing research and development suggest a future where FCEVs could play a key role in the transition to more sustainable mobility. The combination of fuel cells with energy storage systems in hybrid vehicles (FCHEVs) represents an effective strategy for optimizing the performance and efficiency of this technology.

2.4.3 Battery

2.4.3.1 Battery Basics

A battery is a device that converts chemical energy into electrical energy and vice versa. The term battery generally refers to a single cell, a battery module, or a battery pack. A cell is the fundamental unit consisting of electrodes (anode and cathode), separators, terminals, electrolyte, and a casing [90]. A battery is often a group of cells connected in series and/or parallel, including support functions, a control unit, and thermal management, designed for a specific application.

The fundamental principles behind the operation of a battery are based on electrochemistry. The battery operates through one or more electrochemical cells. Each cell consists of two electrodes, the anode (negative pole during discharge) and the cathode (positive pole during discharge), immersed in an electrolyte, a medium that conducts ions [24, 90]. The electrodes are electrical conductors that provide a surface for chemical reactions. The functioning of the battery is based on spontaneous oxidation-reduction (redox) reactions during discharge. At the anode, an oxidation reaction occurs, where a material loses electrons. These electrons flow through an external circuit (the load). At the cathode, a reduction reaction occurs, where a material gains electrons from the external circuit. Simultaneously, positively or negatively charged ions move through the electrolyte between the electrodes, completing the internal circuit. The figure shows a simple scheme of a battery.

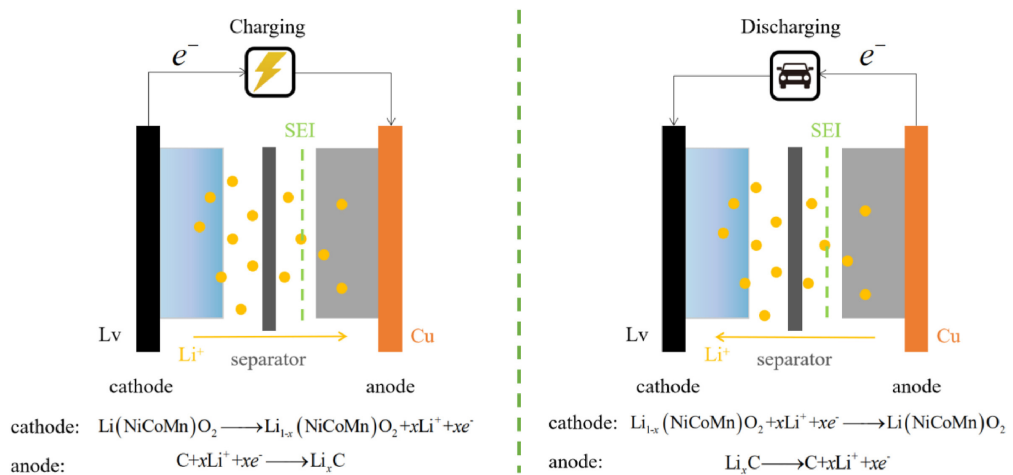


Figure 2.11: Working principle of lithium-ion battery from [296].

During discharge, the chemical energy stored in the electrode materials is converted into electrical energy due to the flow of electrons. The capacity of a battery is the amount of electric charge (usually measured in ampere-hours, Ah) that can be extracted from a fully

charged battery under specific discharge conditions [76, 313]. The reverse process occurs during charging (in the case of rechargeable batteries), where electrical energy supplied by an external source is converted back into stored chemical energy in the electrode materials. In this case, the cell functions as an electrolytic cell. The difference in electrical potential between the anode and the cathode determines the cell voltage. The voltage of a battery depends on the materials used in the electrodes and the electrolyte [24]. Several types of batteries are used in electric vehicles (EVs), each with its own characteristics and applications. The main battery types are: lead-acid, nickel metal-hybrid (NiMH), lithium-ion (Li-Ion), sodium-nickel chloride (Na-NiCl), lithium-sulfur (Li-S), Lithium-Air (Li-Air), Sodium-Air (Na-Air), and Graphene batteries.

Lead-acid batteries are the oldest technology used in early electric vehicles. They are inexpensive to produce and have a high power-to-weight ratio [187]. However, they have disadvantages such as handling acidic substances, the presence of lead, a low energy-to-weight ratio (30-50 Wh/kg), and a low energy-to-volume ratio. They also have a limited cycle life (around 1500 cycles) [107], and reduce in some applications to less than a few hundred cycles.

Nickel metal hydride (NiMH) can be seen as a further development of nickel-cadmium (NiCd) technology, which is now forbidden from being used in vehicle applications due to its heavy metal cadmium content [24]. NiMH cells typically have low internal resistance, enabling deep cycling with hundreds of thousands of cycles achievable across a broad state of charge range. This robust technology tolerates rapid charging and discharging across diverse temperatures. However, during storage and unmonitored use, gas emissions (O_2 and/or H_2) can occur, making safety vents essential in the cell design for protection. NiMH batteries exhibit a voltage depression phenomenon rather than the true memory effect typical of NiCd batteries [24]. This voltage depression can appear as a rapid drop in voltage, even though the actual capacity loss is minimal. It is linked to prolonged overcharging or repeated partial discharges, which cause a phase transition in the $NiOOH$ electrode. Unlike the memory effect, which makes the battery "remember" the previous discharge capacity, voltage depression in NiMH batteries is a distinct phenomenon that can be managed by fully discharging the cells or occasionally leaving them in an open-circuit state.

Currently, lithium-ion batteries are the most widely used in electric vehicles due to their high energy density (100-265 Wh/kg), high power density, long cycle life (>1000 cycles), low self-discharge rate, and relatively low weight [313]. Various cathode chemistries are used in EV lithium-ion batteries, including lithium cobalt oxide (LCO), lithium manganese oxide (LMO), lithium iron phosphate (LFP), lithium nickel manganese cobalt oxide (NMC), and lithium nickel cobalt aluminum oxide (NCA). Anode materials also vary, with graphite, carbon-based materials, and lithium titanate (LTO) being the most common. Lithium-ion cells can consist of cells in different formats: cylindrical, prismatic, and pouch cells, as shown in Figure 2.12. The two former cells have a hard-case cell, while the pouch can be manufactured in different geometric shapes like round, triangular, etc [260].

Sodium-nickel chloride (Na-NiCl) batteries, often referred to as Zebra batteries, are a technology similar to sodium-sulfur (Na-S) batteries. Their main advantage is that they can provide up to 30% more energy at low temperatures, although their optimal operating range is between 260°C and 300°C [259]. The Na/ $NiCl_2$ battery offers advantages such as a wider operating temperature range, lower metal corrosion, and higher power density. They are also known for their high energy density.[175].

Lithium-air (Li-air) batteries, often (and inaccurately) called lithium-oxygen batteries, rely on the oxidation of lithium at the negative electrode and the reduction of oxygen (ideally from the air) at the positive electrode. The main advantage of a lithium-air cell is its extremely high theoretical energy density, although the practical energy density, considering

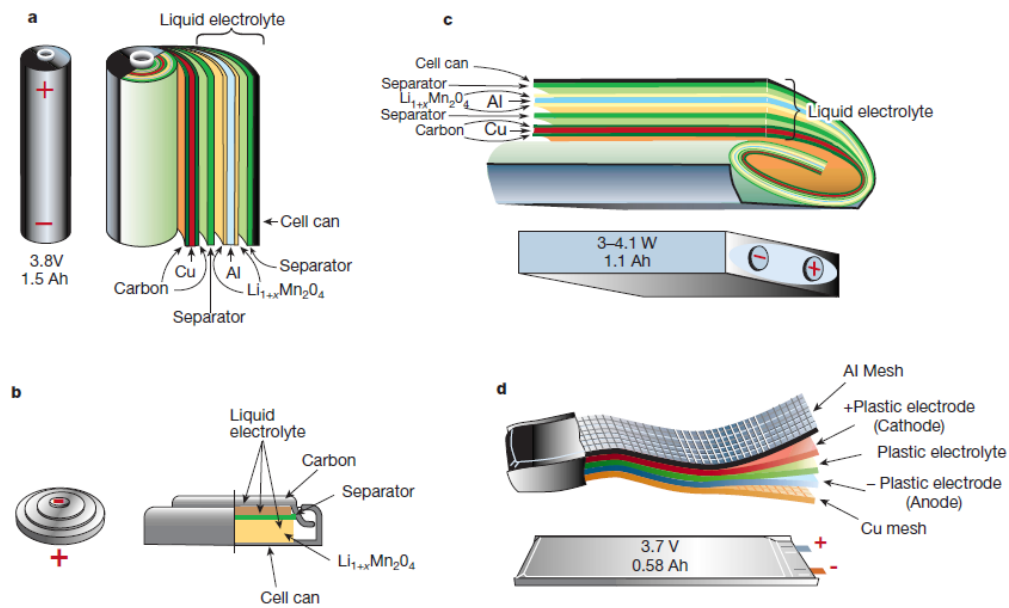


Figure 2.12: Different Lithium-Ion cell design, from [278]. **a)** Cylindrical, **b)** coin, **c)** prismatic, and **d)** pouch.

all factors, is likely two to three times higher than that of lithium-ion cells [24]. These batteries offer very high energy and power density but suffer from a low cycle life [325].

Sodium-air (Na-air) batteries present a promising alternative for electric vehicles. The company BASF has developed a sodium-air battery with an energy density of 4.5 kWh/L [259]. In electric vehicles, this type of battery could multiply the range of current lithium batteries by at least thirteen times. A major advantage of these batteries is that sodium is the sixth most abundant element on Earth. They offer advantages in rechargeability compared to lithium-air batteries, and room-temperature sodium-air battery chemistry is currently under study. These batteries provide very high energy density and high power density.

Graphene batteries take advantage of the unique properties of graphene, a pure carbon material with high thermal conductivity and extreme lightness [259]. One of the main advantages of graphene-based batteries is that they barely heat up, allowing for fast or ultra-fast charging without significant power losses due to heat. The Spanish company Graphenano has created a graphene battery that, when integrated into a GTA Spano vehicle (900 HP), enabled a range of 800 km and could be charged in just 5 minutes using a high-power outlet [259]. This type of battery is still in an early development stage, although prototypes with a specific power of 1 kWh/kg exist, and it is expected to soon reach 6.4 kWh/kg.

Lithium-ion batteries (LIBs) are the most widely used among all battery types due to a combination of superior characteristics. First, they offer high energy and power density, enabling the development of lightweight and compact batteries, which are ideal for portable devices and essential for the range of electric vehicles [38, 175]. Additionally, LIBs boast a long cycle life and a low self-discharge rate, ensuring prolonged usability over time [175]. Their fast-charging capability, wide operating temperature range, and lack of memory effect make them particularly versatile for various applications. Compared to conventional technologies such as lead-acid, Ni-Cd, and Ni-MH batteries, LIBs exhibit greater energy efficiency. The ability to optimize their chemistry, performance, and safety features for specific requirements has further solidified their dominant position in the market. Figure 2.13 illustrates the power density vs energy density for different energy sources for vehicle traction.

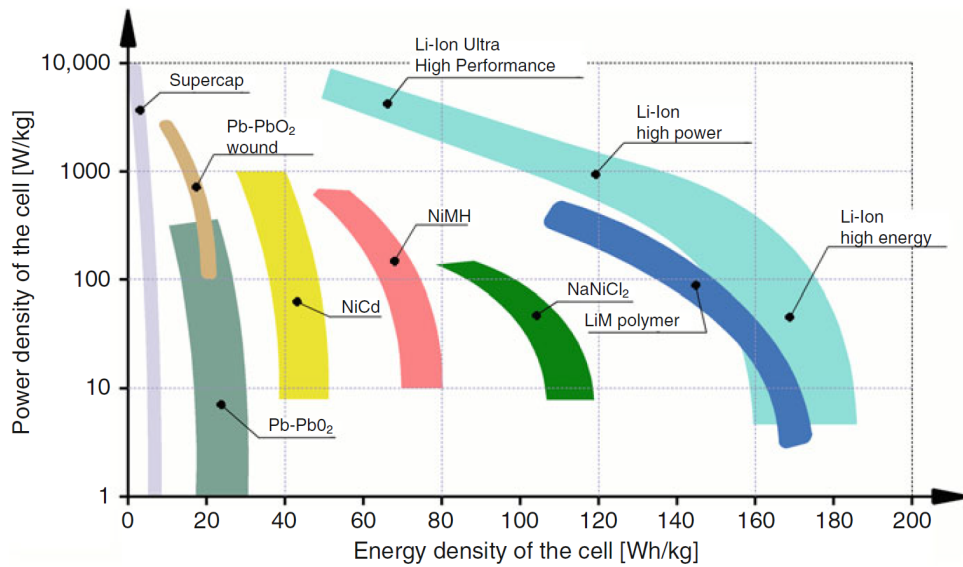


Figure 2.13: Ragone plot of energy sources for vehicle traction from [126].

Battery safety is of the utmost importance in electric vehicles due to the large number of cells they contain. Various chemical and electrochemical reactions occur during the battery's charging and discharging process [280]. The increase in temperature within large cells poses a significant challenge when they are used at high discharge rates. Batteries generate more heat during rapid charge and discharge sequences at high current intensities, such as those occurring during harsh acceleration [180, 280]. The increasing size of batteries and the formation of larger packs can lead to significant challenges related to thermal stability. Excessive localized temperature rise can reduce battery cycle life and initiate thermal runaway [280]. Thermal runaway in a battery is defined as an uncontrolled and self-accelerating increase in temperature within a cell, which can trigger a chain reaction of heat generation and, in extreme cases, lead to explosions or fires [243]. This phenomenon occurs when the rate of heat generation exceeds the battery's ability to dissipate heat, often triggered by abusive conditions such as overcharging, over-discharging, internal short circuits, or physical damage [323]. Thermal runaway is a positive feedback process: the rise in temperature further accelerates exothermic reactions, releasing even more heat. This poses a serious safety risk for batteries and the vehicles that use them.

Electric vehicle batteries are subject to degradation, which primarily manifests as a decrease in capacity (capacity fade) and a decrease in power (power fade) [24]. Degradation can be classified into two main categories: calendar aging and cycle aging. The former aging occurs over time, regardless of battery use, and is influenced by factors such as storage temperature and state of charge (SOC) [165]. Passenger vehicles, which remain parked most of the time, are more dependent on calendar life. The degradation by cycle aging is caused by the battery's charge and discharge cycles, and is influenced by factors such as temperature during the cycle, charge/discharge rate (Crate), and depth of discharge (DoD) [165]. Vehicles that are used frequently are more dependent on cycle life. The lifespan of electric vehicle batteries is a crucial aspect. The average lifespan of batteries in electric vehicles tends to be around 8-10 years, defined by a degradation of 20% - 30% of the battery's capacity relative to its initial capacity [256]. The end of life (EOL) of an automotive battery is generally defined as when its capacity drops below 80% of its nominal capacity [165]. Cycle life refers to the number of charge/discharge cycles the battery can perform under specific operating conditions. Lithium-ion batteries can exceed 1000 charge cycles [187]. Several factors influence the lifespan of batteries, including temperature, DoD, Crate, and

State of Charge (SoC). Optimal operating temperatures are generally between 25 and 40°C [280]. High temperatures (above 50°C) can reduce charging efficiency and negatively impact lifespan. Low temperatures can also deteriorate ion transport properties, thus, a battery pre-heater should be implemented to extend the battery life in colder climates. High discharge and charge rates can drastically reduce battery lifespan [256], and keeping the battery at high or low SOC levels for prolonged periods can accelerate calendar degradation [165].

2.4.3.2 Battery Parameters

The battery capacity refers to the total charge discharged by the activated material at an electrode when a battery is fully exhausted [135, 317]. The C-rate is the discharge (or charge) current divided by the battery's nominal capacity and is a measure of the speed at which a battery is charged or discharged relative to its maximum capacity. A C-rate of 1C means that applying that value of amperes will discharge the entire capacity of the battery in one hour. A C-rate of 2C means it will discharge the battery in half an hour, and so on. The C-rate is defined via the following formula:

$$C_{\text{rate}} = \frac{I}{Q_n} \quad 2.16$$

where I is the charge or discharge current, and Q_n is the battery's nominal capacity in ampere-hours (Ah).

State of Charge (SOC) refers to the amount of energy available in a battery compared to its maximum capacity [314]. It is usually expressed as a percentage, and a fully charged battery has an SOC of 100%, and a fully discharged battery has an SOC of 0%. SOC is a key parameter for the Battery Management System (BMS) and provides a reference for charge/discharge control and cell balancing. It is closely related to other battery states. SOC is the fraction of the maximum capacity that is still available to be delivered. Alternatively, it is defined as the ratio between the battery's residual capacity under standard discharge conditions and its nominal capacity under the same conditions. SOC can be estimated by integrating the current over time. The current is the rate of change of charge:

$$i(t) = \frac{dq}{dt} \quad 2.17$$

where i is the current, and q is the charge, then the instantaneous SOC is equivalent to the charge remaining at the positive electrode:

$$dSOC = -dq = -i(t) dt \quad 2.18$$

and integrating over time, the expression for the state of charge is obtained:

$$SOC(t) = SOC_0 - \int_{t_0}^t i(\tau) d\tau \quad 2.19$$

where SOC_0 is the state of charge at the time t_0 . The SOC is usually expressed as a percentage of the maximum battery capacity, resulting as follows:

$$SOC(t) = \frac{SOC_0 - \int_{t_0}^t i(\tau) d\tau}{Q_T} \cdot 100 \quad 2.20$$

where Q_T is the maximum theoretical capacity of a battery (in Coulombs) derived by Faraday's law of electrolysis [135]. The depth of discharge (DOD) is the fraction of battery capacity removed from the fully charged state, and can be defined as follows:

$$DOD = 1 - SOC \quad 2.21$$

State of Health (SoH) indicates the current condition of the battery relative to its ideal initial condition (Beginning of Life - BOL) [314]. It reflects the extent of aging of the battery and is an indicator of the battery's remaining capacity relative to its initial capacity. SoH is influenced by various factors such as internal impedance, capacity, power density, and self-discharge rate. SoH is the ratio between the actual (aged) capacity (Q_{aged}) and the initial (nominal) capacity (Q_{new}). It can also be defined based on changes in internal resistance. The SoH can be described by the following equations:

$$SoH = \frac{Q_{\text{aged}}}{Q_{\text{new}}} \quad 2.22a$$

$$SoH = \frac{R_{\text{EOL}} - R}{R_{\text{new}} - R} \quad 2.22b$$

where R_{EOL} is the battery resistance at the end of life, R_{new} is the resistance at the beginning of life, and R is the current battery resistance. State of Energy (SoE) represents the ratio of the remaining energy in the battery to the nominal energy [314]. While SOC is often used to estimate remaining energy, SoE also takes into account the load current profile and energy losses due to heat generation at high currents, which SOC alone does not capture. SoE is influenced by SOC, SoH, temperature, and future operating conditions. SoE is the ratio of the remaining energy ($E_{\text{remaining}}$) in the battery to the nominal energy E_{rated} as follows:

$$SoE = \frac{E_{\text{remaining}}}{E_{\text{rated}}} \quad 2.23$$

The precise calculation of a battery's State of Energy (SoE) is essential for forecasting the battery's available driving range of an electric vehicle, a key factor in alleviating the prevalent range anxiety among EV drivers. SoE can be calculated by the power integral method, open circuit voltage (OCV) method, neural networks (NN), and model-based method.

Remaining useful life (RUL) is the estimation of the remaining time or number of cycles before a battery reaches the end of its useful life (end of life - EOL) [76]. EOL is typically defined as a certain performance decline, such as a reduction in capacity to 80% of the initial value. Predicting RUL is complex due to the multifactorial nature of battery degradation. SoH is often used to estimate RUL, and there is no simple, universal formula for RUL. Its estimation is based on aging models, historical usage data, operating conditions, and the current state of the battery (mainly SoH). Various approaches, including empirical, semi-empirical, and machine learning (ML)-based models, are used to predict RUL.

State of Power (SoP) represents the peak power capacity that the battery can deliver or absorb within a given time frame [314]. It is an important parameter for electric vehicles (EVs), especially for safety control and regenerative braking. Accurate estimation of SoP is crucial for optimizing power management in the vehicle and ensuring battery safety during acceleration and braking. SoP is influenced by SOC, SoH, and State of Safety (SOS). SoP indicates the peak power capacity of the battery over a given period. For systems that require specific power, the State of Function (SoF), which seems to be used interchangeably with or related to SoP in some sources [24, 49, 115], can be defined as a logical variable (yes/no) indicating whether the battery can meet the power demands. A SoF definition is given as [178]:

$$SoF = \frac{P - P_{\text{demand}}}{P_{\text{max}} - P_{\text{demand}}} \quad 2.24$$

where P is the possible power that the battery can supply, P_{demand} is the power demand, and P_{max} is the maximum possible supplied power of the battery (at SOC and SoH equal to 0). An SoF equal to 0 means the battery hardly meets the power demands.

Finally, it is important to note that these states are interconnected. For example, SoP is determined by SOC, SoH, and SOS (safety state). SoE is influenced by SOC and SoH. RUL is closely related to SoH. SOC is essential for estimating and controlling other states [2]. SoH affects the usable capacity of the battery and thus the SOC for a given amount of energy. SoF (or SoP) depends on the estimated values of SOC and SoH, the charge/discharge profile, and the operating temperature. Understanding these states and the factors influencing them is crucial for effective management of lithium-ion batteries in electric vehicles and other applications. The BMS plays a key role in accurately estimating these parameters to ensure optimal performance, safety, and battery longevity [49, 314].

2.4.3.3 Battery Modeling

There are several main approaches to battery modeling, each with its own characteristics in terms of accuracy, computational complexity, and setup effort. There are three main types of battery modeling [322]: white-box models (i.e. electrochemical model), grey-box models (e.g., reduced-order model and equivalent electric circuit models, EECMs), and black-box models (e.g., Neural Network model). The electrochemical models are based on the physical and chemical laws governing the internal electrochemical processes of the battery, such as concentrated solution theory and porous electrode theory [170, 322]. They offer an accurate representation of battery degradation processes through complex partial differential equations. Examples include the Pseudo-Two-Dimensional (P2D) model [64] and the Single Particle Model (SPM) [277]. They are useful for battery design and sensitivity analysis. However, they require extensive parameterization and considerable computational power, making them less suitable for real-time applications. The Equivalent Circuit Models (ECM) use ideal circuit components such as resistors, capacitors, and voltage sources to simulate the electrical behavior of the battery [170, 294, 322]. They are characterized by low complexity and high computational efficiency, making them suitable for implementation in Battery Management Systems (BMS) in real-time [2, 294]. Examples include the Rint model (internal resistance), the Thévenin model (with one or more parallel RC circuits), and models incorporating Warburg impedance to represent diffusion effects. Figure 2.14 illustrates four common equivalent circuit models. Model parameters can be identified using techniques such as Electrochemical Impedance Spectroscopy (EIS) or system identification methods like current pulse tests [90]. They can be adaptive if parameters are updated online [90].

Empirical Models (Black-box) rely on parameterized functions or models trained on experimental data. They are simple and have a low computational cost, but do not provide insights into the underlying physical phenomena, and their accuracy may be limited to operating conditions similar to those used for calibration [151]. Examples include look-up tables and polynomial functions.

Data-driven models (Black-box) use machine learning (ML) algorithms and historical data techniques to determine battery degradation patterns [322]. They require a large amount of high-quality data to achieve good performance and can suffer from overfitting. They offer flexibility in adapting to real operational data. Examples include neural networks.

Mixed Electrochemical-Thermal models integrate both electrical and thermal aspects of battery behavior. They allow consideration of the influence of temperature on electrical parameters and vice versa, improving the accuracy of voltage estimation and battery state prediction, particularly in high-current applications with rapid temperature fluctuations [175, 280].

Reduced Order Models (ROMs) are derived from full electrochemical models using dis-

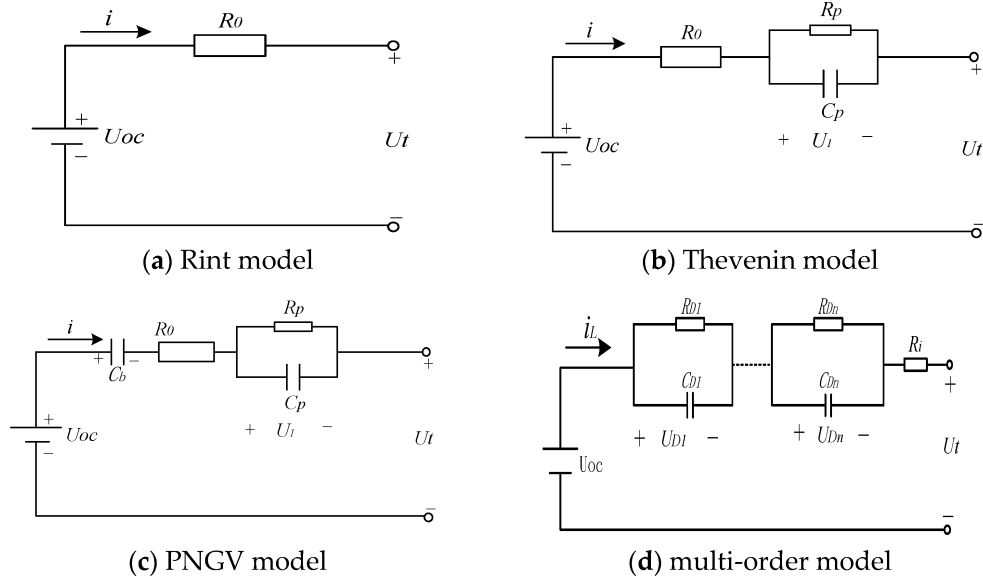


Figure 2.14: Common integer-order equivalent circuit models from [326].

cretization techniques to reduce computational complexity while maintaining an acceptable level of fidelity [90, 175, 322]. They are useful for applications requiring fast computation and real-time implementation, such as BMS for electric vehicles (EVs).

In conclusion, the choice of the most suitable modeling approach depends on the specific application, the required accuracy, the available computational resources, and the need to understand the battery's internal physical phenomena.

2.5 Electric rotating machines

2.5.1 Electric rotating machines for traction

An electric rotating machine is an electromechanical device that converts mechanical energy into electrical energy (operating as a generator) or electrical energy into mechanical energy (operating as a motor). Most practical electric machines achieve this conversion through the action of a magnetic field. Electric machines can be rotating, such as motors and generators, which have a stator and a rotor separated by an air gap, or static, such as transformers, which transfer electrical energy from one circuit to another through a magnetic field without moving parts. These devices play a fundamental role in generating, distributing, and utilizing electrical energy.

Electric motors for traction can be classified based on their operating principle into DC (direct current) motors and AC (alternating current) motors. DC motors include variants with brushes, characterized by high torque at low speeds but limitations at high speeds and maintenance issues, and brushless DC (BLDC) motors, which offer greater reliability and efficiency with electronic commutation [105]. AC motors include induction motors (IMs), robust and widely used, and synchronous motors, which are further divided into permanent magnet synchronous motors (PMSMs), preferred for high performance and efficiency [39, 105], reluctance motors (SRMs) with a simple structure, and wound rotor synchronous motors (WRSMs), less common. Based on the structure of the magnetic flux, motors can be classified into radial flux motors (RFM), where the flux travels radially between the stator and rotor, and axial flux motors (AFMs), in which the stator and rotor are stacked axially and the flux is directed axially. The latter can be either induction (AFIM) or permanent

magnet (AFPM) and come in various configurations depending on the number of stators and rotors. Figure 2.15 shows the taxonomy for the AC motors.

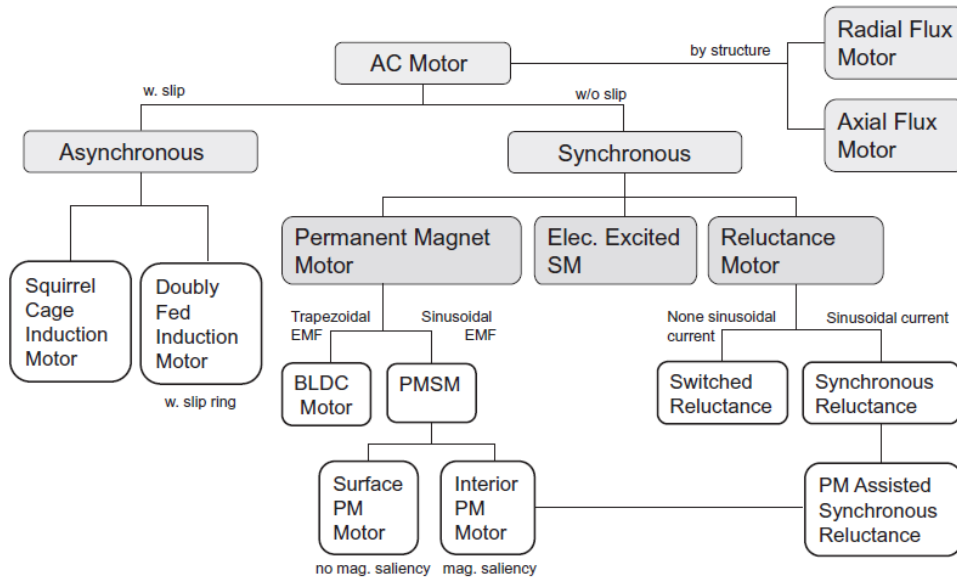


Figure 2.15: Taxonomy of AC motors, from [206].

DC motors were initially the primary choice for electric vehicle traction. Among their advantages and features, a reasonable torque-speed curve stood out, with maximum torque at low speeds, a wide speed range at constant power, and ease of control [105]. Their speed was relatively simple to control by varying the terminal voltage [169]. Moreover, DC motor technology was technologically mature, and its manufacturing cost was relatively low compared to other electromechanical machines. Their ability to achieve high torque at low speeds made them suitable for traction requirements. Additionally, in the early years of the automotive industry, electric vehicles were often powered by DC systems supplied by batteries, making the use of DC motors logical [196]. However, DC motors have several limitations that led to their decline for road traction. These include bulky construction, low efficiency, low maximum speed, and lower reliability. In particular, the presence of commutators and brushes causes wear and friction problems, requiring periodic maintenance [105, 139]. At high speeds, maintaining contact between the brushes and commutator becomes problematic, with the risk of sparks, overheating, or commutator fusion. Additionally, DC motors generally have lower power density at higher speeds. For these reasons, brushless AC motors are now preferred for high-performance and high-power applications in electric vehicles [58].

The fundamental difference between synchronous and asynchronous motors lies in the rotor rotational speed relative to the stator magnetic field. In asynchronous (or induction) motors, the rotor rotates at a slightly lower speed than the synchronous speed of the stator's field, due to the slip phenomenon required to induce current in the rotor [10]. In contrast, in synchronous motors, the rotor rotates exactly at the same synchronous speed as the stator's magnetic field, maintaining constant synchronization. The induction motors (IM), which are a type of asynchronous motor, are mainly of two types: squirrel cage, and wound rotor. Squirrel cage motors are the most common due to their simplicity, robust construction, lower cost, and brushless operation, which reduces the need for maintenance [159]. Wound rotor motors have rotor windings connected to slip rings, allowing external resistances to be inserted into the rotor circuit. This offers better control of the starting torque and speed, but at the cost of increased complexity and maintenance [159]. Induction motors are valued

for their reliability and robustness. They are capable of providing good starting torque and are suitable for a wide range of applications. Additionally, their well-established technology and large-scale production make them economically competitive. However, they have some limitations for electric traction. They generally have lower efficiency compared to permanent magnet synchronous motors (PMSM), especially at partial loads, since part of the power is dissipated in the rotor to induce current [139]. Furthermore, their control can be more complex to achieve high performance in terms of efficiency and dynamics compared to synchronous motors. The rotor speed is always lower than the synchronous speed due to the slip required to generate torque.

Synchronous motors are AC motors in which the rotor rotates at the same speed as the stator's magnetic field, i.e., at synchronous speed. The rotor is synchronized with the stator field, and there is no slip under steady-state conditions. Various types of synchronous motors are used or considered for electric traction: Permanent Magnet Synchronous Motors (PMSMs), Synchronous Reluctance Motors (SynRMs), and Wound Rotor Synchronous Motors (WRSMs). Figure 2.16 shows several categories of synchronous motors, from a pure reluctance motor to a pure magnet motor. PMSM uses permanent magnets mounted on the rotor to create the rotor's magnetic field. They offer high efficiency and power density, along with a good torque-to-weight ratio [159]. They can be further classified based on the magnet position (surface-mounted SPMSM, interior IPMSM) and the shape of the back electromotive force (sinusoidal or trapezoidal/BLDC). PMSMs are increasingly used in electric vehicles for their superior performance [41]. However, they may be more expensive than induction motors due to the use of permanent magnets, especially those containing rare earth materials. SynRM does not use permanent magnets but instead exploits the variation of the rotor's magnetic reluctance with its position relative to the stator field to generate torque [206]. They can potentially be cheaper than PMSMs because they do not require permanent magnets and have good tolerance to high temperatures [244]. However, they may have lower power density and generate more noise and vibrations compared to PMSMs. WRSM is similar to wound rotor induction motors, but the rotor circuit is excited by an external DC source via slip rings [70]. These motors can offer flexible reactive power control and the ability to operate with a unit power factor or leading, useful for power factor correction in the grid. However, the presence of slip rings leads to maintenance and lower reliability compared to brushless motors. They are less common in modern road electric traction systems.

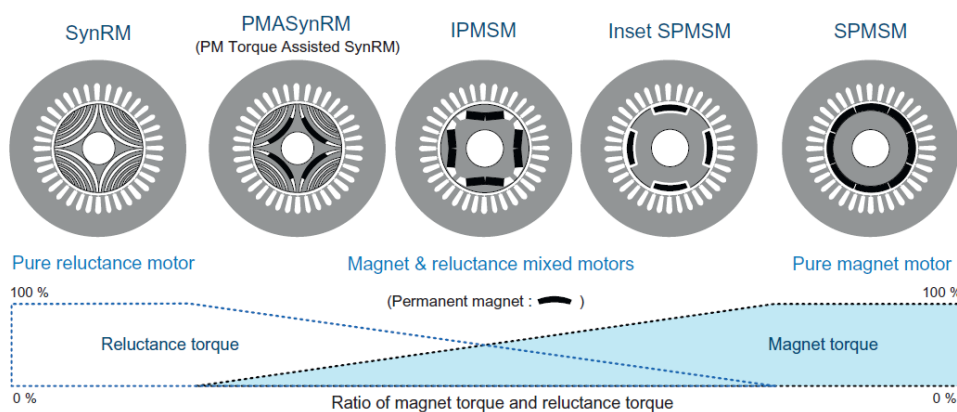


Figure 2.16: Several categories of synchronous motors, from [152].

In summary, while induction motors offer robustness and generally lower cost, synchronous motors, particularly PMSMs, are preferred for electric traction due to their higher efficiency and power density, which contribute to greater vehicle range and performance.

The development of power electronics has made it possible sophisticated control AC motors, overcoming some of the initial complexities associated with their use. Synchronous reluctance motors represent an interesting alternative for applications where cost and resistance to high temperatures are critical factors.

In axial flux motors (AFM), the stator and rotor are stacked axially, and the magnetic flux lines travel axially along the shaft axis. This configuration differs from radial flux motors, where the magnetic flux travels radially between the stator and rotor, as shown in Figure 2.17.

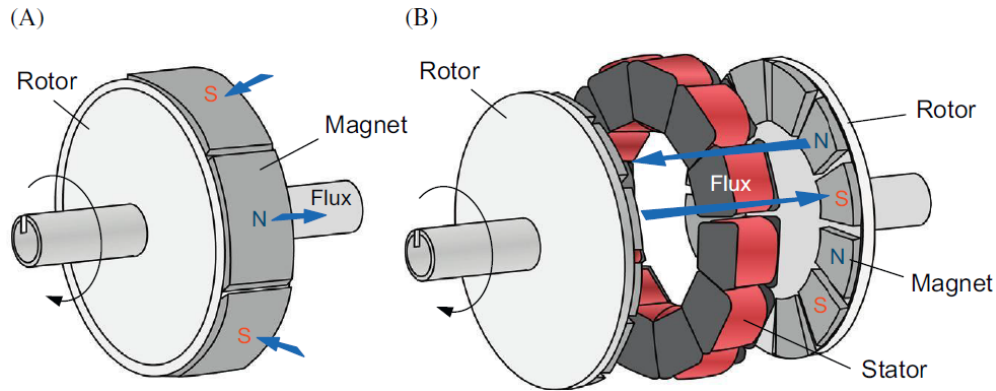


Figure 2.17: PMSM configurations, from [152]. (A) Radial-flux type and (B) axial-flux type.

A distinctive feature of AFMs, particularly AFPM (Axial Flux Permanent Magnet) versions, is their high torque density and reduced axial length compared to the outer diameter [96]. This compact "pancake" shape facilitates integration with other electromechanical components, making it suitable for applications requiring high torque density. The TORUS topology (single interior stator with two external rotors) for AFPM motors is considered the best in terms of power density/torque and efficiency, thanks to the optimal use of copper and reduced losses. The TORUS-NS (single interior stator with two external rotors North-South) configuration can be housed within the wheel, allowing direct power transfer and increasing efficiency by eliminating mechanical components such as the transmission [161]. Axial flux motors are considered a valid alternative to traditional radial flux motors for the traction of electric vehicles, especially in applications requiring high torque and compactness [96]. They are particularly suitable for integration as in-wheel motors (IWM), where axial space is limited. This direct-drive configuration offers potential mechanical simplification and efficiency improvement. Even when not directly integrated into the wheel, the small thickness of AFMs can facilitate installation near the wheels, reducing the length of drive shafts and related losses. Several companies have developed direct-drive in-wheel applications based on PMSM motors. However, for some applications, such as small city cars, the radial diameter size of AFMs could pose a limitation [235]. Furthermore, most variants of permanent magnet axial flux motors (AFPM) have poor flux weakening capability [96], which can limit the Constant Power Speed Ratio (CPSR) required in certain traction applications. In conclusion, axial flux motors represent a valid and promising solution for electric propulsion, especially for applications that benefit from their compact shape and high torque density, such as in-wheel motors. Axial flux permanent magnet (AFPM) motors, particularly the TORUS configurations, seem to be the most suitable for traction, although managing flux weakening remains an important aspect to consider. Axial flux switched reluctance machines (AF-SRM) motors offer an interesting alternative.

In conclusion, for traction, an electric motor must possess several key characteristics: first and foremost, it must have a high power and torque density to ensure adequate performance in terms of acceleration and the ability to overcome inclines [206, 244]. High efficiency across a wide range of speeds and torque is also crucial to maximize vehicle range, providing high torque at low speeds for quick starts and hill climbing, and high power at high speeds for cruising. Equally important are a wide Constant Power Speed Ratio (CPSR), quick dynamic response, robustness, and high reliability to operate under various conditions, along with a reasonable cost [244]. The ability for regenerative braking is essential to recover energy, along with good controllability, low noise levels, minimal torque ripple, compact size and weight, high overload capacity, and ideally, fault tolerance. Figure 2.18 shows the power density for several types of motors; notable is the high peak power of the axial flux motor compared to the other motors.

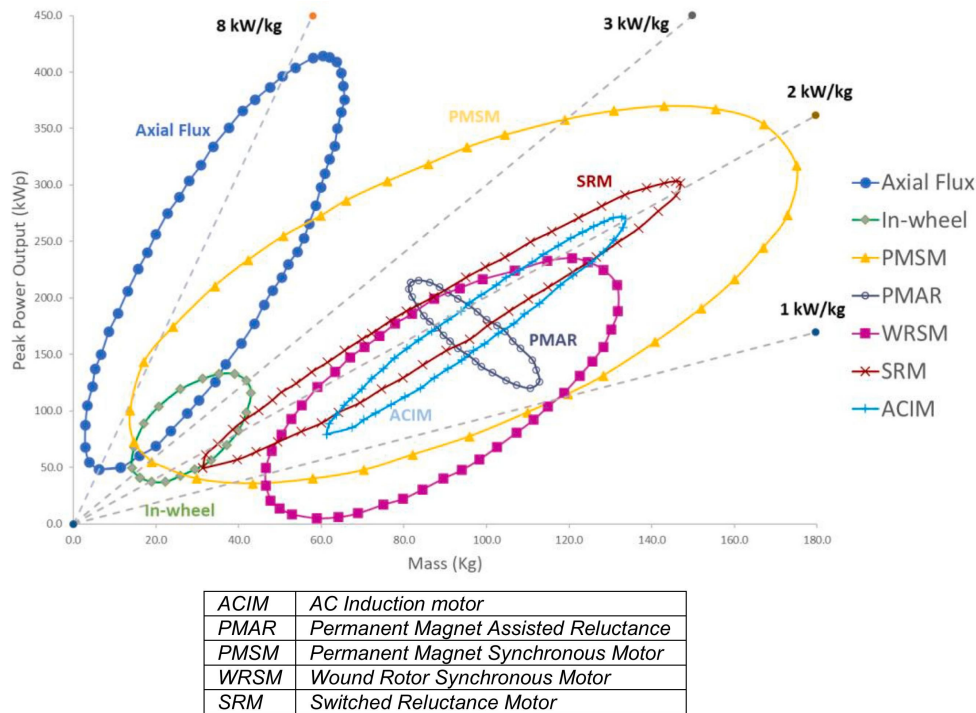


Figure 2.18: Power-density comparison of different motor types recently used in EVs, from [105]. The x-axis represents the motor’s mass (kg), and the y-axis is the motor’s peak power output (KW).

2.5.2 Motor sizing and efficiency

The generation of torque in a Surface-Mounted Permanent Magnet (SMPM) motor primarily results from the interaction between the magnetic field generated by the permanent magnets and the stator’s magnetic field. The dq reference frame is used to transform three-phase electrical quantities (a, b, c) into a two-dimensional (d, q) system linked to the rotor or the magnetic field [29]. This simplifies the motor equations, decoupling torque and flux control, making current regulation more efficient with strategies like Field-Oriented Control (FOC). The fundamental torque equation for PMSMs is given by the product of flux (Ψ) and current (I) vectors [206, 219, 290] as follows:

$$\begin{aligned}
T_{em} &= \frac{3P}{2} \frac{1}{2} (\vec{\Psi} \times \vec{I}) = \frac{3P}{2} \frac{1}{2} (\Psi_d i_q - \Psi_q i_d) = \\
&= \frac{3P}{2} \frac{1}{2} \left(\underbrace{(L_d - L_q) i_d i_q}_{\text{reluctance torque}} + \underbrace{(L_{dq} i_q^2 - L_{qd} i_d^2)}_{\text{induction torque}} + \underbrace{\Psi_m i_q}_{\text{excitation torque}} \right) \quad 2.25
\end{aligned}$$

where P is the number of poles, Ψ_d and Ψ_q are the d-axis and q-axis flux, i_d and i_q are d-axis and q-axis currents, L_d and L_q represents the d-axis and q-axis inductances, L_{dq} and L_{qd} represents the cross-coupling inductances, and Ψ_m is the permanent magnets flux. In an isotropic machine or non-salient poles, L_d is equal to L_q , thus the reluctance torque is zero. For a pure synSM, the flux due to the permanent magnets is zero, so the excitation torque is zero.

Surface Permanent Magnet Synchronous Motors (SPMSMs) can be controlled to deliver maximum torque up to the inverter voltage limit using strategies such as Maximum Torque per Ampere (MTPA) [199, 206]. In this operating region, the current is managed to maximize the torque produced per ampere of stator current while minimizing copper losses [206]. As the motor speed increases and the back electromotive force approaches the inverter voltage limit, the system enters the maximum power region. To increase speed beyond this point without exceeding the voltage limit, field weakening control is implemented. This is typically achieved by applying a negative d-axis current in the dq reference frame, which counteracts the flux generated by the permanent magnets, reducing the total air-gap flux and consequently lowering the back electromotive force [206]. In this field weakening region, motor torque decreases as speed increases, while the delivered power remains approximately constant. This control strategy optimally utilizes the inverter capabilities and extends the motor operational speed range. Figure 2.19 shows the EV motor torque-speed stationary characteristic.

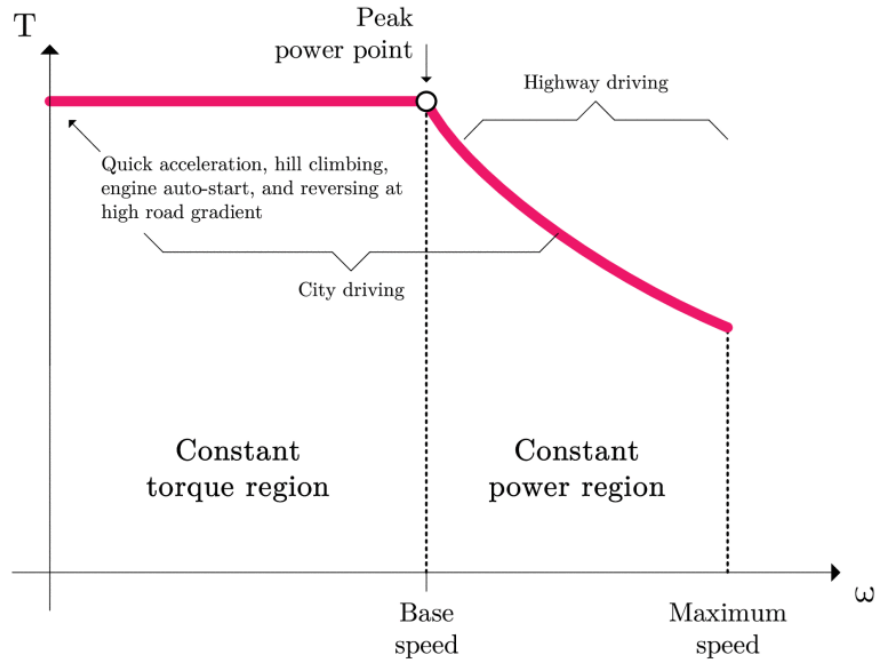


Figure 2.19: Qualitative torque-speed stationary characteristic for an EV and most frequent operating points, from [195]

One notable aspect of the torque generation in PMSMs is the phenomenon of constant torque operation, which spans from zero speed to the base speed (ω_{base}). This region is

characterized by a linear increase in power. In the constant power region, which occurs above the base speed, the torque gradually decreases as the speed increases, allowing the motor to operate at much higher speeds than it could in the constant torque region.

It is assumed here that all the air gap power is converted into mechanical power, and dividing the power by the rotor speed, the torque can be expressed as [124, 206]:

$$T \propto k_w B_m A_m V_{\text{rot}} \quad 2.26$$

where k_w is the winding factor, B_m is the magnetic load (T), A_m is the electric load (A/m), and V_{rot} is the rotor volume. The winding factor is a coefficient less than or equal to one that accounts for the reduction in the induced voltage or magnetomotive force in an electrical machine due to the distribution of the windings across the slots and the use of short-pitched (or fractional) coils [236]. The electric loading, also known as specific electric load, is a measure of the amount of electrical current per unit of circumferential length of the armature (typically the stator) in an electrical machine [29]. The magnetic loading is a measure of the amount of magnetic flux per unit surface area in the air gap of an electrical machine. The electric and magnetic loading are limited by the material's properties, and by the temperature rise and available cooling. Therefore, once the motor type and cooling approach are selected, B_m and A_m are nearly locked in. The key variable left is rotor volume. With a larger diameter, both the current and the flux increase, while a longer length results in only in flux increment, keeping constant electric and magnetic loading.

Because the power air gap is equal to the torque times the rotor speed, there are two solutions to increase the power. From the relation in Equation 2.26, the torque is proportional to the rotor volume; so, for the same power, as the volume reduces, the rated speed increases. So high-speed motors have smaller volumes, but also low max torque. Furthermore, a high-speed motor might need a reduction gear stage to match the motor speed with the vehicle speed.

The efficiency of an electric motor (η) is generally defined as the ratio between the mechanical output power and the electrical input power. Mathematically, it can be expressed as [248]:

$$\eta = \frac{P_{\text{out}}}{P_{\text{in}}} = \frac{T\omega_r}{T\omega_r + P_{\text{loss}}(T, \omega_r)}, \quad T \geq 0 \quad 2.27a$$

$$\eta = \frac{P_{\text{out}}}{P_{\text{in}}} = \frac{T\omega_r - P_{\text{loss}}(T, \omega_r)}{T\omega_r}, \quad T < 0 \quad 2.27b$$

where P_{out} is the mechanical output power (the product of torque T and rotor angular velocity ω_r), P_{in} is the electrical input power, P_{loss} represents the total losses in the motor. The total losses (P_{loss}) in an synchronous machine permanent magnet (SMPM) electric motor can be classified into different categories [248, 249]: copper or joule losses (P_{Cu}), iron or core losses (P_{Fe}), mechanical losses (P_{mech}), and other losses or stray losses. Copper losses are due to the resistance of the stator and rotor windings. However, in SMPM motors, the rotor does not have significant conductive windings contributing to Joule losses, except for eddy currents induced in the magnets or rotor material. The stator copper loss is given by [199]:

$$P_{\text{Cu}} = 3I_s^2 R_s \quad 2.28$$

where R_s is the stator phase resistance and I_s is the RMS phase current. Iron losses occur in the stator and rotor's iron core due to magnetic flux variations and mainly consist of

hysteresis and eddy current losses [199, 206]. These latter losses are modeled individually and then summed to describe the total iron losses as follows:

$$P_{\text{Fe}} = P_{\text{h}} + P_{\text{eddy}} + P_{\text{exc}} \quad 2.29$$

where P_{h} are the hysteresis losses, P_{eddy} are the eddy losses, and P_{exc} are the excess losses. Hysteresis losses are commonly modeled considering the energy dissipated as the magnetic field in a ferromagnetic material cycles [290]. This energy is proportional to the area enclosed by the hysteresis loop in the B-H plane. Empirically, hysteresis loss is often approximated using equations like [206]:

$$P_{\text{h}} = K_{\text{h}} f B_{\text{max}}^{\alpha} \quad 2.30$$

where K_{h} is a constant, f is the frequency of excitation, B_{max} is the peak value of the flux density. Both K_{h} and α can be empirically determined and depend on the properties of the ferromagnetic material and volume. Typically, values of α are 1.5-1.6.

Eddy current losses are power losses that occur in conductive materials, particularly in the ferromagnetic core of electrical machines and transformers, when subjected to a time-varying magnetic field. This magnetic field induces circulating electrical currents within the material, known as eddy currents. Due to the electrical resistance of the material, these currents dissipate energy in the form of heat. Eddy current losses are a significant component of iron losses [236]. The eddy current losses can be modeled as [194, 206]:

$$P_{\text{eddy}} = K_{\text{e}} f^2 B_{\text{max}}^2 \quad 2.31$$

where K_{e} is a constant coefficient determined experimentally. Finally, the excess losses appear only because the classical calculation of eddy current losses ignores the presence of domains and domain wall motion [155]. Physically, excess losses can be identified as the result of competition between the external magnetic field and local reaction fields caused by eddy currents or other microstructural interactions. The excess losses can be described as [155, 229]:

$$P_{\text{exc}} = K_{\text{a}} (f B_{\text{max}})^{\frac{3}{2}} \quad 2.32$$

where K_{a} is the excess losses coefficient. In summary, excess losses account for a portion of iron losses that cannot be fully explained by hysteresis losses and classical eddy current losses [206]. They are related to complex magnetic phenomena at the microstructural level of the material.

Mechanical losses in an electric motor refer to power losses associated with rotor rotation. The main causes of these losses are bearing friction and air resistance (windage) [206]. In general, mechanical losses are often proportional to rotor speed for bearing friction and proportional to the cube of speed for ventilation losses. A general model for mechanical losses may include terms proportional to different powers of speed [85], here formulated as:

$$P_{\text{mech}} = c_{\text{mech},0} + c_{\text{mech},1}\omega_{\text{r}} + c_{\text{mech},2}\omega_{\text{r}}^2 + c_{\text{mech},3}\omega_{\text{r}}^3 \quad 2.33$$

where $c_{\text{mech},x}$ can be found experimentally.

Stray losses, also called additional losses, represent the difference between the total losses of an electric machine and the sum of stator and rotor resistive losses (copper losses), core losses (iron losses), and mechanical losses [236]. They are caused by various phenomena, some of which are easy to model, while others are very difficult to calculate accurately. The main causes of stray losses include: spatial harmonics of the windings and slot harmonics, skin and proximity effects in conductors, and magnetic flux leakage and non-uniform distributions of current and flux. The calculation of stray losses is difficult and does not guarantee

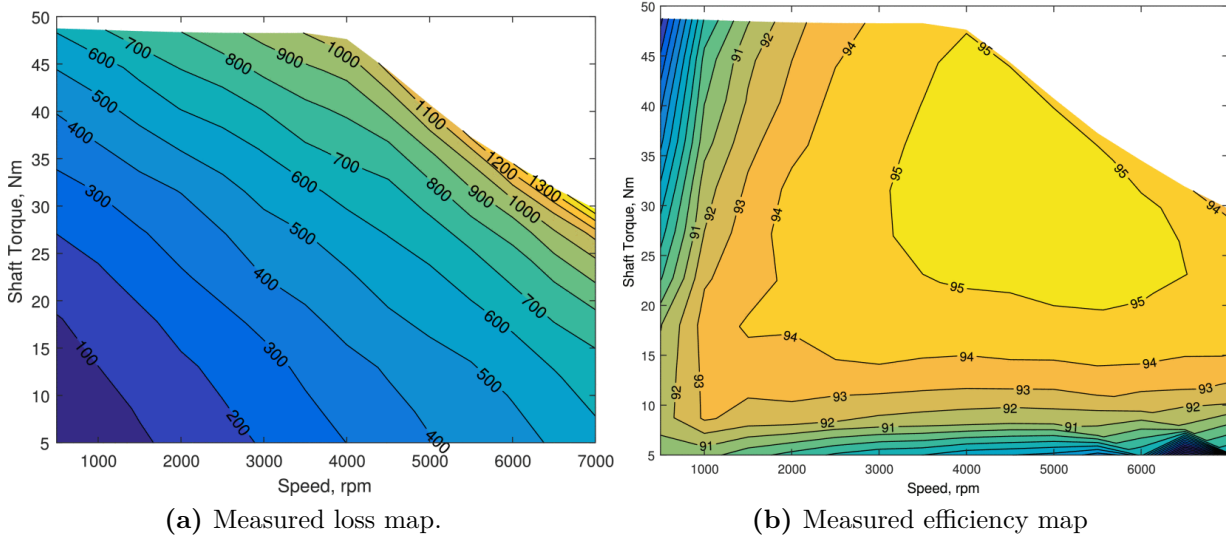


Figure 2.20: Example of losses and efficiency maps for SMPM, from [274].

satisfactory accuracy [206]. In practice, they are often roughly estimated using empirical coefficients [236]. Figure 2.20 shows the losses and efficiency maps as a function of the shaft torque and the rotor speed.

The power losses in an electric machine can also be expressed as a sum of polynomial terms as a function of torque (T) and angular speed (ω_r) [183, 185]. The main idea is that different types of losses in the motor can be individually approximated or combined through these polynomial terms. These latter terms constitute a model for the total motor loss at a given operating point defined by torque and speed. The total motor loss is then expressed as the sum of multiple polynomial terms as [183]:

$$P_{\text{loss}}(T, \omega_r) \approx \sum_{m,n} k_{mn} T^m \omega_r^n \quad 2.34$$

where m and n are integer exponents and k_{mn} are constant coefficients. The summation extends over different integer values of m and n (e.g., from 0 to 3 or 4), and the coefficients k_{mn} are determined through curve fitting of data obtained via finite element analysis (FEA) or experimental loss measurements [183, 185].

In summary, using polynomial equations of the form $k_{mn} T^m \omega_r^n$ represents an effective approach for modeling losses in electric machines. This method allows for analyzing the contribution of different loss sources, generating efficiency maps, and supporting the motor design and optimization process for specific applications.

2.5.3 Scaling Laws

Scaling laws are based on the idea of predicting the performance of a new design using data from an existing and similar design, through geometric and winding modifications [271, 273].

Axial scaling modifies the axial length of the motor (l_{stk} or l_{Fe}) using an axial scaling factor (k_A) [271, 275]. The cross-section of the lamination remains unchanged. It is assumed that the axial length of the stator, rotor, and magnets changes in the same proportion. So the stack length of the scaled motor became:

$$l_{\text{stk}} = l_{\text{stk},0} k_A$$

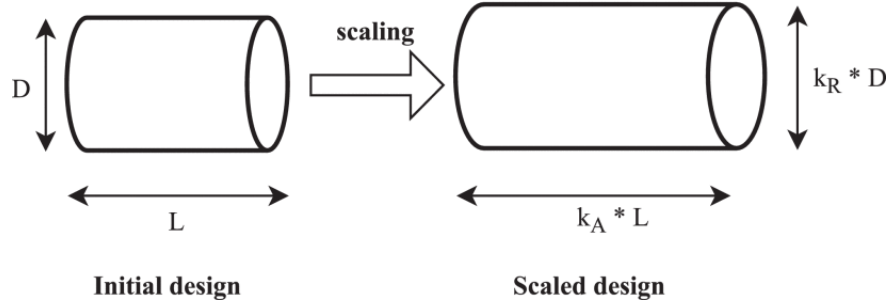


Figure 2.21: Radial scaling and axial scaling, from [275].

Radial Scaling modifies the radial dimensions of the motor (such as the outer diameter D_{out}) using a radial scaling factor (k_R) [271, 275]. The lamination is altered proportionally, creating a new "geometrically similar" lamination. The outer diameter of the scaled machine becomes:

$$D_{\text{out}} = k_R D_{\text{out},0}$$

During radial scaling, the current density in the slot (J) must be adjusted to preserve magnetic flux density, according to the relationship [273]:

$$J = \frac{1}{k_R} J_0$$

where J_0 is the reference current density.

Winding Scaling (Rewinding) modifies the number of turns per coil (N_c) and the number of parallel paths (a_p) using a winding scaling factor (k_W) with the following expression [273, 275]:

$$\frac{n_c}{a_p} = k_W \frac{N_{c,0}}{a_{p,0}}$$

where $N_{c,0}$ and $a_{p,0}$ are the reference number of turns of coil and the number of parallel paths, respectively. This is done to adapt the motor to the required terminal voltage. Figure 2.21 shows the impact of radial and axial scaling coefficients on the electric machine.

Scaling laws establish how the dimensions and performance parameters of the scaled motor relate to those of the reference motor. For a more detailed explanation, consult the work [271, 273, 275]. Table 2.4 reports the key scaling principles for synchronous machine permanent magnet (SMPM) and axial flux motor (AFM):

Table 2.4: Scaling Laws for SMPM and AFM

Symbol	SMPM	AFM	Description
T_{shaft}	$k_R^2 k_A T_{\text{em},0}$	$k_R^3 k_A T_{\text{em},0}$	Torque shaft
P_{shaft}	$k_R^2 k_A P_0$	$k_R^3 k_A P_0$	Power shaft
P_{Cu}	$k_A P_{\text{Cu}0\text{co}} + k_R P_{\text{Cu}0\text{ew}}$	$k_R^3 k_A P_{\text{Cu},0}$	Copper losses
I_{ph}	$\frac{k_R}{k_W} I_{\text{ph},0}$	$k_R I_{\text{ph},0}$	Phase current
R_{ph}	$k_R^2 k_A R_{0\text{co}} + \frac{k_W^2}{k_R} R_{0\text{ew}}$	$k_R k_A R_{\text{ph}}$	Phase resistance
V	$k_R^2 k_A V_0$	$k_R^2 k_A V_0$	Volume

The scaling laws assume the same level of magnetic saturation in both the reference and scaled motor, implying that the lamination design should remain the same or be proportionally scaled. Furthermore, scaling procedures aim to preserve the specific electric loading.

The provided scaling laws are not intended for scaling over a very wide geometric range due to the natural variation in the optimal slot fill ratio between small, medium, and large machines [273]. Technological limits exist for scaling, such as the maximum allowable axial length. In such cases, radial scaling may also be required to achieve the desired torque. Scaling laws can provide high accuracy compared to FEA calculations, but they are derived and applicable only in situations where magnetic flux density levels are preserved after scaling [275]. Finally, radial scaling requires adjusting the current density in the slot to maintain the specific electric loading

In conclusion, the scaling laws for permanent magnet motors, including SPMSMs, allow for estimating the characteristics of a scaled motor based on a reference design using axial (k_A), radial (k_R), and winding (k_W) scaling factors. The primary motor dimensions are closely linked to the required torque and power. It is important to consider the limitations of these laws, particularly for large geometric scaling, and to maintain magnetic saturation levels and specific electric loading. Applying these laws can significantly reduce the time required for designing and optimizing a series of motors [271].

2.6 Driveline

2.6.1 Gear box

In electric vehicles (EVs), the transmission system is crucial in transferring power from the electric motor to the wheels, significantly impacting performance, energy efficiency, and driving experience [252]. Unlike internal combustion engine (ICE) vehicles, which require complex multi-speed transmissions to operate the engine within its optimal efficiency range [73, 188], electric vehicles thanks to the characteristic torque-speed curve of electric motors (which provide maximum torque at low speeds and a wide operating speed range) [252, 269, 284] can often use simpler transmissions [252]. However, the adoption of more sophisticated gearboxes is becoming increasingly relevant to optimize performance and efficiency further [181, 269]. Although many current EVs use a single-speed transmission [181, 252, 269, 284], several other types of gearboxes have been developed or are under research for specific applications in electric vehicles [181]: Manual transmissions (MT), automated manual transmissions (AMT), dual-clutch transmissions (DCT), automatic transmissions (AT), and continuous variable transmissions (CVT), Infinitely Variable Transmissions (IVT), and Magnetic Gear Transmissions (MGT). Furthermore, transmission can be divided into single-speed transmission and multi-speed transmission. The former transmission is the most common solution, featuring a fixed reduction ratio between the motor and the wheels [252]. The simplicity of this system translates into lower costs, reduced weight, and increased reliability [252, 269].

The electric motor, with its high torque available from zero RPM, enables smooth acceleration without the need for gear shifts. Additionally, it allows energy recuperation throughout the entire braking process without interruptions [284]. However, a motor designed for a fixed transmission ratio might be oversized to ensure high starting torque [284]. The multi-speed transmissions use multiple gear ratios (typically two or three). These latter transmissions aim to keep the electric motor and inverter operating in a more efficient range, improving overall energy efficiency [181]. They can also enhance vehicle acceleration, gradeability (ability to climb slopes), and top speed [181, 269]. Various multi-speed gearbox architectures have been adapted from ICE vehicles, including the previously mentioned: automated manual transmissions (AMT), dual-clutch transmissions (DCT), automatic transmissions (AT), and continuous variable transmissions (CVT). These latter transmissions are shown in Figure

2.22.

Manual transmission is less common in pure electric vehicles but may be used in specific applications. The AMT is derived from manual transmissions, which use actuators to automate clutch engagement/disengagement and gear selection. They may experience torque interruptions during gear shifts. The AT is best suitable for internal combustion engine vehicles due to its use of a torque converter. The DTC utilizes two separate clutches to pre-select the next gear, enabling quick and smooth shifts without torque interruption. They are more complex and costly than AMTs. An I-AMT is a variant of the AMT, except that it includes a clutch to connect the second gear rather than a synchronizer. The continuous variable transmission (CVT) offers an infinite number of gear ratios within a given range. The main advantage is the ability to keep the motor consistently in its highest efficiency region. However, traditional CVTs may have lower efficiency than gear-based transmissions in some operating conditions. Infinitely Variable Transmissions (IVT) are similar to CVTs but with a potentially wider transmission ratio range, due to the lowest gear ratio of a CVT can be reduced to zero or even negative by adding a fixed ratio and a planetary gearset, creating a transmission where the ratio of input to output speeds can be infinite [181]. Finally, Magnetic Gear Transmissions (MGT) is an emerging technology that uses magnetic fields to transmit torque, offering potential advantages in reducing wear and noise compared to mechanical gearboxes. They are still in the development and validation phase. MGTs can have different topological configurations like external/internal spur gears, worm gears, rack and pinion, etc [62]. More complex structures have been investigated as well, like cycloidal MGs [65], combining axial and radial topologies, or conical coaxial magnetic gears [190].

The gear ratio is the relationship between the angular input shaft/gear velocity of a gearbox to the output shaft/gear rotational speed, and is described as follows:

$$\tau = \frac{\omega_{\text{in}}}{\omega_{\text{out}}} \quad 2.35$$

where ω_{in} , and ω_{in} are the input and output rotational speed respectively. The gear ratio indicates how much the speed or torque is modified through the gear system. Some sources define the gear ratio as the speed ratio between the output and input speeds. It is important to note the possible inversion in the definition among different sources. In a single gear pair, the gear ratio is also defined as the ratio of teeth on the driven gear (output) to those on the driving gear (input):

$$\tau = \frac{Z_{\text{out}}}{Z_{\text{in}}} = \frac{d_{\text{out}}}{d_{\text{in}}} \quad 2.36$$

where Z_{out} , d_{out} , Z_{in} , and d_{in} are the number of gear teeth and diameter for the output and input gearboxes, respectively. Neglecting the losses, the ratio between the input and output torque is inversely proportional to the speed ratio, indeed, the power balance between input and output follows that:

$$\eta P_{\text{in}} = \eta T_{\text{in}} \omega_{\text{in}} = P_{\text{out}} = T_{\text{out}} \omega_{\text{out}} \quad 2.37$$

where T_{in} is the input torque, T_{out} is the output torque, and η is the efficiency. Thus, for an ideal efficiency, the following holds:

$$\tau = \frac{T_{\text{in}}}{T_{\text{out}}} \quad 2.38$$

In complex transmission systems with multiple gears, such as multi-speed gearboxes, the total gear ratio is the product of the gear ratios of the individual gear pairs. For a gear train, the total gear ratio can be calculated as the product of the number of teeth on the driven gears divided by the product of the number of teeth on the driving gears.

$$\tau_{\text{tot}} = \tau_1 \tau_2 \dots \tau_n \quad 2.39$$

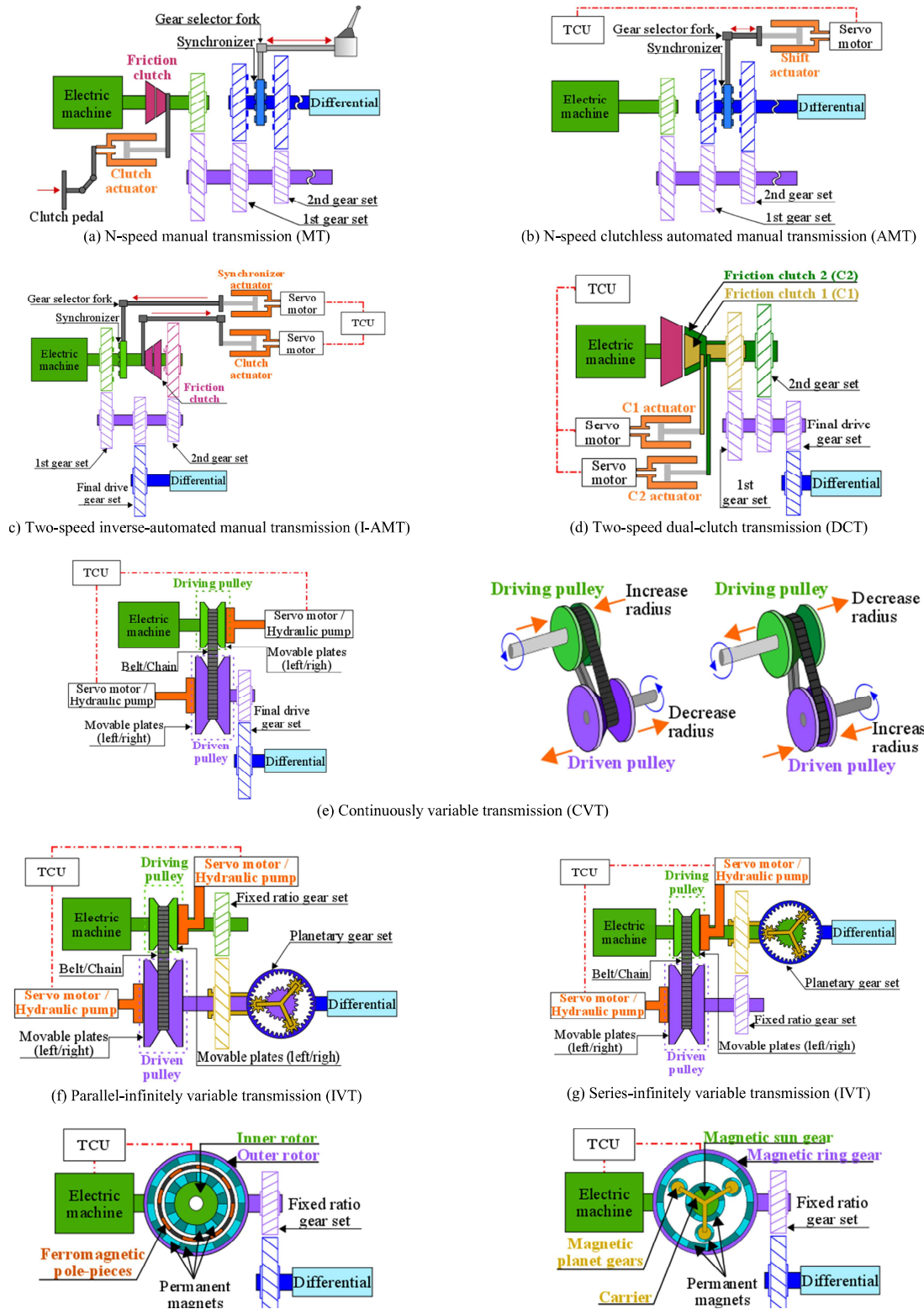


Figure 2.22: Gearbox Topologies for battery electric vehicles, from [181].

Selecting the gear ratio (or multiple gear ratios in multi-speed systems) is a crucial aspect of electric vehicle powertrain design. Various factors must be considered to achieve the optimal balance between performance and efficiency [181, 269]. The vehicle performances, described in detail in the section 4.6, are the gradeability, top speed, energy efficiency, and riding range. The lowest transmission ratio (first gear in a multi-speed system) is often

selected to meet acceleration from a standstill and the vehicles ability to climb certain slopes [135].

A higher (numerically) gear ratio provides more torque to the wheels, improving acceleration and climbing capability [210]. The highest transmission ratio (final gear in a multi-speed system or the only ratio in a single-speed system) is chosen to reach the desired top speed while keeping the motor within its speed limits and an acceptable efficiency range. A lower (numerically) transmission ratio allows for higher speeds, in contrast with the gradeability [135]. Transmission ratio selection significantly impacts the efficiency of the electric motor and inverter. The goal is to operate the motor as often as possible in its highest efficiency regions for the expected driving cycles [284]. In multi-speed systems, intermediate ratios are selected to further improve efficiency and avoid excessive jumps between gears, which could lead to rougher or longer shifts. Enhancing energy efficiency through a well-chosen transmission ratio directly contributes to maximizing the vehicle's range. Various studies modeled multi-gear drivetrains, showing efficiency increased from 0 to 23.3% for setups with two to four gear ratios, while CVT was noted for potentially decreasing efficiency by 4% or upping it by as much as 31.8%, with a wide range of results reported across different studies [181]. Advanced optimization techniques, such as dynamic programming and exhaustive search, can be used to identify the optimal transmission ratios that minimize energy consumption while meeting performance requirements [32]. Designing the gearbox for electric vehicles requires careful evaluation of trade-offs between simplicity, cost, performance, and energy efficiency. While single-speed transmissions provide a robust and cost-effective solution for many applications, adopting multi-speed systems, CVTs, or emerging technologies like MGTs can lead to significant improvements in efficiency and driving dynamics, depending on the vehicles specific needs and target market. Finally, selecting the appropriate transmission ratio is a complex optimization process that must consider a wide range of interconnected factors to ensure optimal performance and maximize the efficiency of the electric vehicle.

The inefficiencies present in gearboxes and related powertrain elements are influenced by various factors such as speed, load, and temperature [113]. Gearbox losses can be categorized as gearing, bearing, sealing, synchronizer, clutch, oil drag, windage, and idling losses, with modeling varying based on detail level [34]. Gearing losses occur at the contact interface between gear teeth due to friction during meshing. Bearing losses originate from friction within the bearings that support the rotating shafts of the gearbox. Sealing losses are caused by friction in the sealing rings used to retain lubricant inside the gearbox and prevent contaminants from entering. Synchronizer losses occur during gear shifts when synchronizers are used to equalize gear speeds before engagement. Clutch losses are present in transmissions with a clutch. In dry clutches, the main losses arise from aerodynamic resistance (windage losses). In dual-clutch transmissions (DCTs), significant losses occur due to the slip required during engagement and disengagement. Wet clutches have different losses related to fluid viscosity. Oil Drag or lubrication losses result from the movement of gears and other rotating components through the lubricating oil, including churning and oil compression effects. They depend on speed, oil viscosity, and lubricant level. Windage losses or aerodynamic losses are due to the air resistance on rotating components, becoming more significant at high speeds. Idling/Spin losses that occur in gears and other rotating components that do not transmit significant loads [102].

Different approaches are described in sources for modeling gearbox losses: analytical component modeling [32], efficiency maps [102], quasi-static and dynamic modeling [113], affine loss models, detailed gear contact analysis [251], and Computational Fluid Dynamics (CFD) for oil drag [48]. The choice of modeling method depends on the required accuracy, model complexity, and specific application. For system-level simulations focused on energy consumption, simpler efficiency maps or affine loss models may suffice. For gearbox component

design and detailed analysis, more complex analytical or numerical methods are necessary. Since this work focuses on powertrain sizing, efficiency methods, and affine methods are sufficient for this task and are described here, leaving it to the reader to explore further details through other sources. The efficiency maps are developed for the entire gearbox or individual gears based on operating parameters such as input speed and torque. These maps can be obtained experimentally or through detailed simulations. The lost power is then the difference between input and output power, determined by efficiency. The efficiency maps for the operational range of each gear and interpolated during drive cycle simulations to estimate total energy consumption. The losses in gearboxes can be approximately represented by an affine relationship (affine method) between the gearbox's input and output power [113], described as follows:

$$T_{out}\omega_{out} = e_{gb}T_{in}\omega_{in} - P_{0,gb}(\omega_e), \quad T_{in}\omega_{in} > 0 \quad 2.40$$

where T_{out}, ω_{out} , T_{in} , and ω_{out} are the torque and speed input and output respectively, $P_{0,gb}$ is the power needed by the gearbox to idle at motor speed ω_e , and e_{gb} is a coefficient which vary usually from 0.95 to 0.97. Considering the gearbox losses, a constant independent of load and speed is the simple affine method. For a pair of spur gears, the efficiency is between 99% to 99.8%. In general, the gearbox efficiency ranges between 80% for the CVT to 97% for the MT. A comparison between different transmission topologies found that the single-speed average efficiency was the highest (>98%) with the lowest values of mass and cost [181]. On the other hand, the single-speed has lower potential dynamic performance and lower potential drivetrain efficiency due to its nature.

As the number of gears increases, so do the gearbox mass and manufacturing costs. The cost of a gearbox is proportional to its weight at the first approximation. To describe the mass variation for the coaxial two-stage passenger and commercial vehicle, an equation was developed based on data [208]. The mass of a coaxial two-stage manual transmission (MT) gearbox for passenger and commercial vehicles, denoted in kg, is defined as follows:

$$m_{gb} = 0.199(\tau_{max}T_{in})^{0.669}z^{0.334} \quad 2.41$$

where τ_{max} is the maximum gear ratio, and z is the number of gears. In the same fashion, changing the argument coefficient of the previous equation described the gearbox mass for commercial vehicle multi-range gearboxes with one countershaft. The relative selling transmission price or RSP (the price relative to a manually shifted passenger car transmission) can be modeled in the same manner and for a passenger car transmission is described by the following equation [208]:

$$RSP = 1.723(\tau_{max}T_{in})^{0.439}z^{0.219} \quad 2.42$$

Although Equations 2.41 and 2.42 are valid for passenger cars give important hints on the gearbox impact. An increment of torque and number of gears results in an increment in mass as well as price, and an increment of gearbox mass means more energy consumption as well.

In conclusion, the gearbox plays a crucial role in vehicle propulsion systems, particularly in electric vehicles, as it significantly impacts energy efficiency and overall performance. The single-speed transmission is mainly adopted for electric motorcycles due to its simplicity and low cost. Furthermore, the electric motor is flexible enough to allow high acceleration, and climbing steep gradients at low speeds, and high-speed cruising at high speeds without shifting. Modeling gearbox efficiency and losses is a complex process that involves multiple factors, including gear friction, bearing losses, lubricant resistance, and shift dynamics. Optimizing gearbox design is therefore essential to maximize electric motor efficiency, enhance acceleration and top speed, and reduce energy consumption.

2.6.2 Final drive

The function of the final drive is to connect the output shaft of the gearbox to the wheel. Furthermore provides an additional stage of speed reduction with a constant ratio. For motorcycles, the final drive transmission can be divided into four categories [240]: chain drive, belt drive, shaft drive, and all-wheel drive. The chain and belt drive are mainly used on powered two-wheeled vehicles with transversal engine/motor, while the shaft drive is typically used with a longitudinally mounted engine/motor. The transverse motor and gearbox allow a compact chassis layout, preserving symmetry to the median plane. However, the distance between the gearbox output shaft and the wheel is considerable. Furthermore, this latter distance changes with the compression or rebound of the rear suspension for the classic swinging arm.

The chain drive has three main parts: a sprocket mated to the gearbox output shaft, a sprocket mated to the wheel, and a roller chain that connects them. Chains can only support tension forces, so the torque is delivered only by the upper side of the chain, while the lower side is slack. Due to the wheel's up and down movement, a chain tensioner can be implemented. Chain drives are preferred in sport motorcycles for their superior efficiency compared to belt and shaft drives [35]. In addition, the final speed ratio can be easily changed by changing the sprockets. On the other hand, chain drive requires more maintenance than belt drives, including regular cleaning and lubrication. Chain drives are subjected to speed fluctuation because the chain passes around the sprocket as a series of chordal-links wrapping around sprockets to form polygons rather than circles (polygonal effect or action) [93]. The polygonal effect causes fluctuations in the effective chain radius, leading to speed variations and potential noise called chain whine or belt whine [88]. Chain efficiency at low speeds is very high, between 96% to 98%, but can drop significantly at high speeds (above 75 mph) due to inertial tension from centrifugal acceleration, causing efficiency lowering up to 85% and power losses exceeding 7 hp (5.2 kW) [35].

The belt drive is analogous to the chain drive, by replacing the sprockets with two pulleys and the chain with a toothed belt. Modern belts have a metallic core for strength and an external polymeric layer for protection. The belts can be divided into synchronous and asynchronous. The synchronous belts are locked into the pulley by the pulley's geometric shape, to prevent slip, while asynchronous belts transmit force only due to the friction between the belt and the pulley, allowing slip. Belt drives are quieter and with less vibration, cleaner with reduced lubrication, and can last up to three times longer than a well-maintained and properly tensioned chain [192]. These latter advantages are making popular belt drives for electric motorcycles for their quietness, efficiency, and reliability.

The shaft drives are complex systems compared to chain and belt drives, but are more reliable, need almost no maintenance, and are capable of transmitting high torque. The shaft drive is usually jointly implemented with a longitudinal engine/motor and is a double universal joint shaft. One extremity of the shaft is connected to the gearbox with a universal shaft, and the second universal joint is connected to a set of bevel gears. It is possible to avoid a telescopic shaft by accurately positioning the joints to the suspension link pivot point. The shaft drives are less used on sport motorcycles due to their lower efficiency, complexity, and higher weight.

All-wheel drive (AWD) motorcycles are emerging nowadays due to the flexibility of electric drives. Noteworthy is the high ratio between the height center of mass and the wheelbase, which leads to wheelie and stoppie issues before tire adherence limits. While in poor adherence conditions like off-road or wet rides, an all-wheel drive system would be beneficial in terms of traction and stability. Typically, the front wheel is directly driven by a hub motor, and the rear wheel is driven by a motor mounted on the chassis and powered like a con-

ventional motorcycle. Different topologies of all-wheel drive motorcycles can be determined by the number of motors and motor location; some examples of topologies are shown in Figure 2.23. The adoption of all-wheel drive (AWD) in motorcycles offers several potential

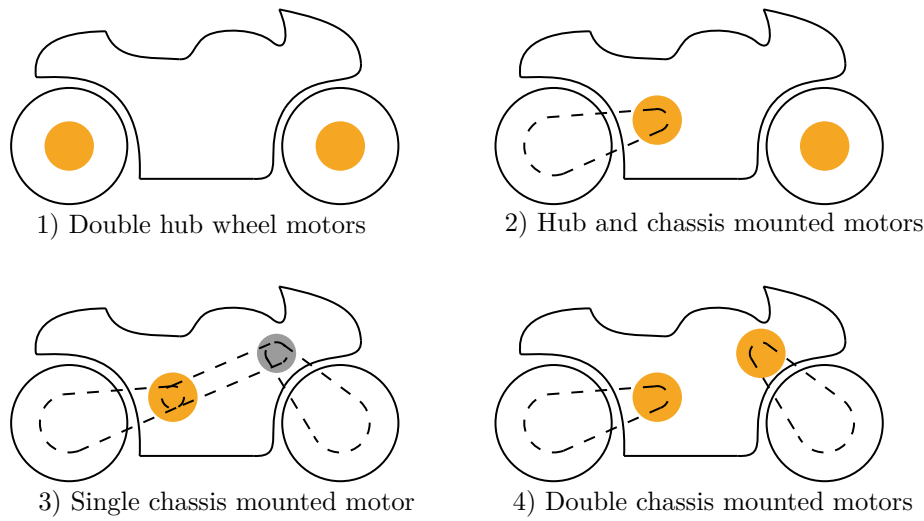


Figure 2.23: All-wheel drive (AWD) motorcycle topologies. On the orange are represented the electric motors.

advantages, especially in specific conditions [177]: increased grip and stability, performance enhancement by proper power distribution during enhancing straight-line and cornering, and higher energy efficiency [108, 166]. Some examples of all-wheel drive electric motorcycles are the Yamaha PES2 and the Armonia DUE-X with both a front hub motor and a rear-mounted motor.

In conclusion, the choice between chain and belt transmissions depends on design priorities and the specific needs of the motorcycle. Chains generally offer higher efficiency and torque transmission but require more maintenance and can be noisier. Belts, on the other hand, are cleaner, quieter, and require less maintenance but may be less efficient at high speeds and need proper tensioning to avoid issues. Finally, the all-wheel drive solution is developing, providing benefits for both traction, safety, and energy consumption.

3. ORIGINAL CONTRIBUTION

3.1 List of publications

- P1. Mirco Bartolozzi, Adelmo Niccolai, Cosimo Lucci, Giovanni Savino, Motorcycle emergency steering assistance: A systematic approach from system definition to benefit estimation and exploratory field testing, *Accident Analysis & Prevention*, Volume 188, 2023, 107116, ISSN 0001-4575, <https://doi.org/10.1016/j.aap.2023.107116>
- P2. Niccolai, Adelmo, Lorenzo Berzi, Francesco Barone, and Niccolò Baldanzini. Analysis of Energy Consumption for Electric Motorcycles Depending on Vehicle Configuration and Driving Cycles. *IOP Conference Series: Materials Science and Engineering* 1306, no. 1 (May 2024): 012032. <https://doi.org/10.1088/1757-899X/1306/1/012032>.
- P3. Niccolai, Adelmo, Lorenzo Berzi, and Niccolò Baldanzini. 2025. "Analysis of Gearbox Losses for High-Performance Electric Motorcycle Applications" *Engineering Proceedings* 85, no. 1: 34. <https://doi.org/10.3390/engproc2025085034>
- P4. A. Niccolai, M. Clemente, T. Hofman, N. Baldanzini, Two-wheel-driven electric super-bike powertrain optimization, *IFAC-PapersOnLine* 59 (5)(2025) 199204, 11th IFAC Symposium on Advances in Automotive Control AAC 2025. doi: <https://doi.org/10.1016/j.ifacol.2025.07.105>

3.2 Discussion

This chapter contains the list of publications produced during the PhD and a description of the original contribution associated with the work. The thesis is based on the previous papers. The first publication [P1] is not reported in this thesis, but part of the vehicle dynamics developed in that work is reported in chapter 4.

The second study [P2] presents a novel and comprehensive analysis of energy consumption in electric motorcycles, considering various real-world driving conditions and operational parameters, like the braking bias. Section 7.1 is in part based on this work. Unlike previous works focusing on theoretical models or specific case studies for cars, our research integrates

experimental data of electric motorcycles with modeling techniques to provide a more accurate and applicable energy efficiency assessment. The study suggests that the rear wheel regenerative motorcycle (RWR) architecture is preferable (less consumption, much simpler, and cheaper) if it is possible to apply a logic where the rear regenerative torque is prioritized. Whereas the 2WR benefit of an almost braking distribution independence on energy reduction. This latter configuration could be better in situations where high decelerations and high adhesion coefficients are required.

In the third study [P3], an approach to characterize the idling losses for a single-speed gearbox for an electric superbike was presented. Chapter 6 is based on this study. The key contributions of this research include: no-load losses experimental characterization and analytical description, influence on consumption depending on two driving cycles (UDDS, WMTC). The study highlights the importance of gearbox losses on low power demanded driving cycles.

Finally, in the fourth study [P4], a framework for the powertrain optimal design was proposed. Section 7.2 is based mainly on this work. The tool developed was applied for designing a two-wheel-driven superbike, jointly optimizing the gear ratio, the motor size, and the battery size, considering performance and adherence constraints. The key contributions were the implementation of propulsive and braking forces repartition strategies to maximize the tire adherence or minimize the rear and front motor losses. On several driving cycles, the results for an optimal design highlight significant energy consumption reduction, up to approximately 22%. The tool allows for evaluating braking strategies, even simpler ones that do not require expensive and complex systems, and evaluating the motorcycle architecture in terms of design.

4. VEHICLE DYNAMICS

4.1 Reference system

The inertia coordinate system was indicated by the coordinates in capital letters (XYZ), and the set of body-fixed coordinates by xyz. These latter coordinates are fixed with the vehicle. Like the SAE Z-up vehicle axis system [47], here the vertical forces (Z-axis) are positive in the upward direction. In the case of planar motion, the vehicle is constrained on the XY plane. The two sets of coordinates are shown in Figure 4.1. Initially, the inertia and body coordinates are aligned, then during the motion, the body coordinates can be obtained from the inertia coordinates via a sequence of rotations by three angles. These latter angles are the roll (ϕ), pitch (μ), and yaw (ψ). The longitudinal, lateral, and vertical vehicle dynamics were analyzed independently and described in the next section.

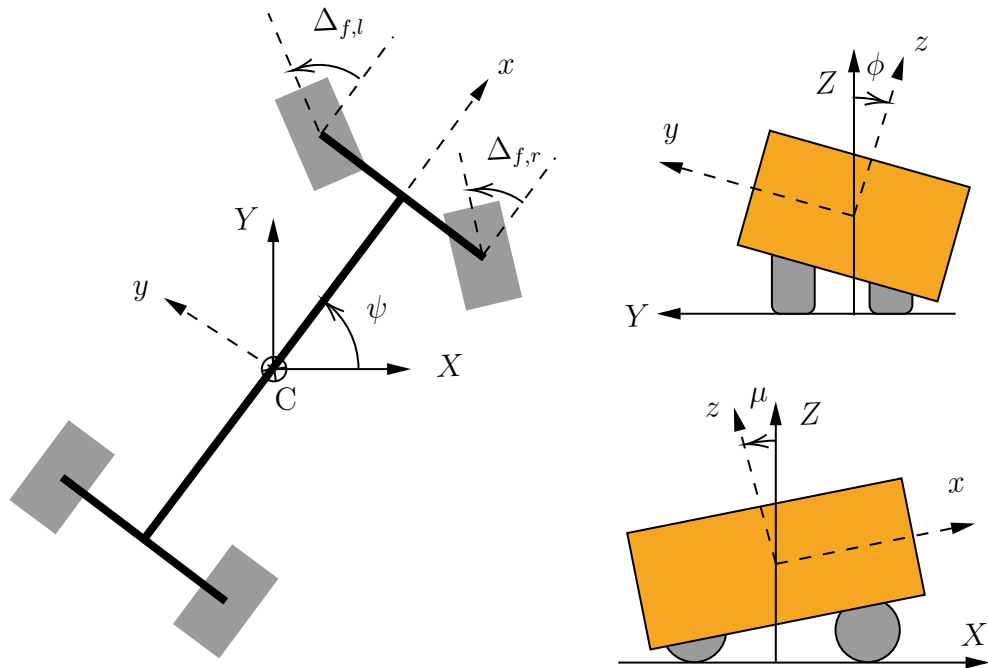


Figure 4.1: Shows the vehicle planar motion on the left, the rear view on the top right figure, and the side view on the bottom right figure.

4.2 Tires

Tires are fundamental components that exchange forces with the ground, due to friction forces, hysteresis, and adhesion. A coordinate system for the tires was defined, and it is shown in figure 4.2

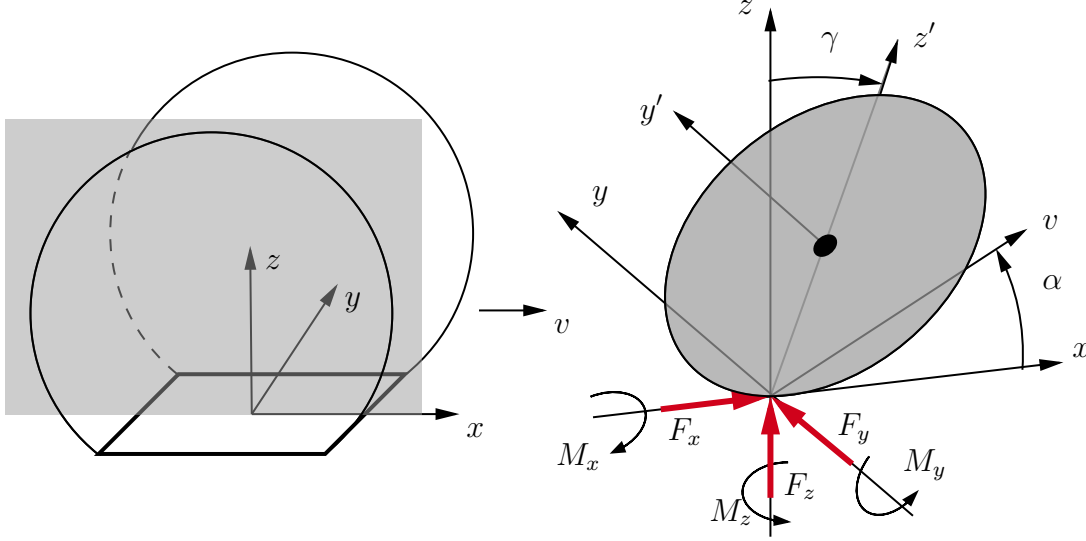


Figure 4.2: Tire coordinates system on the left, the middle tire plane is the area highlighted in gray. On the right picture is shown the middle wheel plane rotated by α along the z-axis (sideslip angle) and inclined by γ (camber). The generic forces acting along the three directions are represented.

According to SAE, the tire longitudinal slip ratio can be described as:

$$k = \frac{\omega_y R_e - v_x}{v_x} \quad 4.1$$

which is the difference between the tires circumferential speed, calculated as the product of its angular velocity (ω_y) and the effective rolling radius (R_e), and the relative speed between the road and the wheel axle, normalized by the latter speed. The sideslip angle (α) is the angle between the travel direction and the heading direction. The tangent of this latter angle corresponds to the ratio between the lateral (v_y) and forward speed of the tire center, as follows:

$$\tan(\alpha) = -\frac{v_y}{v_x} \approx \alpha \quad 4.2$$

This latter expression is usually approximated with the angle itself due to the low values during normal conditions (i.e. $\alpha \leq 8$) [109]. The spin slip (φ) is the ratio between the vertical rotational velocity or yaw rate (ω_z) on the forward speed, as follows [14]:

$$\varphi = -\frac{\omega_z}{v_x} = -\frac{r - (1 - \epsilon_y)\Omega \sin(\gamma)}{v_x} \quad 4.3$$

where Ω is the rotational speed along the wheel spin axis, γ is the camber angle, r is the yaw rate ($\dot{\psi}$), and ϵ_y is the camber reduction factor to correct the tire contact patch flattening due to the normal load. This latter parameter is almost equal to zero for motorcycle tires. The ratio between the yaw rate and the center wheel forward speed is also called turn slip (φ_t).

4.2.1 Rolling resistance

Rolling resistance is called the phenomenon of energy dissipation during tire rolling. This latter resistance is mainly due to the rubber hysteresis of a loaded and unloaded tire. For a resting tire, the distribution of the normal pressure is symmetric to the wheel center, while an upward shift will happen during the roll. Thus, the vertical resultant force is moved upward by a distance (e_x), and shown in figure 4.3.

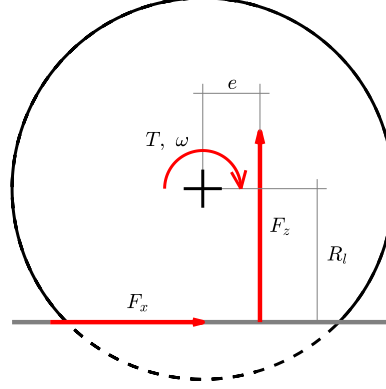


Figure 4.3: Forces and torque acting on the wheel. The vertical and horizontal hub reaction is not shown.

Usually, the rolling resistance is modeled as a longitudinal force acting against the movement and applied to the tire contact patch as follows [109]:

$$F_{rr} = \frac{e_x}{R_l} F_z = c_{rr} F_z \quad 4.4$$

where e_x is the longitudinal arm, R_l is the loaded wheel radius, and c_{rr} is rolling resistance coefficients. The latter coefficient was modeled differently, considering the speed influence, the tire pressure, and the camber angle. For low speed values (far from stationary waves), the rolling resistance is almost constant, and this latter approximation was usually implemented for vehicle modeling.

4.2.2 Longitudinal force

From experimental results, the longitudinal force can be expressed as a function of the longitudinal slip and the vertical load acting on the wheel, for example, the well-known Magic Formula [224]. The steady-state tire behaviour can be modeled by a function with as variable the vertical load (F_z), longitudinal practical slip (k), the sideslip angle (α), camber angle (γ), and the yaw rate (r), that can be written as:

$$F_x = f_x(F_{z,k}, \alpha, \gamma, r) \quad 4.5$$

In case of zero sideslip and camber, with small k values, and neglecting the tire load sensitivity, the longitudinal force can be approximated with a linear function as follows:

$$F_x = C_k k = F_z c_k k \quad 4.6$$

where C_k is the longitudinal slip stiffness or the longitudinal force slope at zero slip, and c_k is this latter stiffness normalized by the vertical load.

4.2.3 Lateral force

Lateral forces are necessary for vehicle handling and are generated when the tire velocity is different from the wheel heading. The angle between these two latter directions is called the sideslip angle (α). A lateral force is also generated when a camber angle is present due to non-uniform tire deformation, and it is called camber thrust or force. As for the longitudinal force, a function of the normal load, the slip ratio, the side slip angle, the camber angle, and the yaw rate:

$$F_y = f_y(F_{z,k}, \alpha, \gamma, r) \quad 4.7$$

From experimental data, different nonlinear functions were developed, but if there are no harsh braking or traction maneuvers (i.e., slip ratio low), and with a small sideslip angle value, the lateral force can be described with a linear function of the sideslip angle and the camber angle as follows [50]:

$$F_y = C_\alpha \alpha + C_\gamma \gamma = (c_\alpha \alpha + c_\gamma \gamma) F_z \quad 4.8$$

where C_α is the tire cornering stiffness, C_γ is the tire camber stiffness, c_α is the normalized cornering stiffness, and c_γ is the normalized camber stiffness.

The camber thrust and the sideslip force could act in opposition or not, according to the angle directions. Thus, for a given camber angle, the sideslip could be null (kinematic steering) or even negative, especially for motorcycles due to their high lean angle needed for the lateral equilibrium.

4.2.4 Moments

Moments act on the tire because the pneumatic tangential and normal stress is not symmetrically distributed about the contact patch center. Thus all the forces could be considered acting on the tire patch center by adding the moments. The moments along the x, y, and z axes are called overturning, rolling resistance, and self-aligning moments, respectively. The lateral force produces a vertical moment along the tire z-axis (M_z), usually called a self-aligning moment. This latter name comes from the tendency to align the tire toward the heading direction. On the z-axis, the camber moment is due to the lateral normal force shift. The distance between the center and the normal force (e_y) is called the camber arm. This latter moment results from the lateral force times the distance from the center patch, called the pneumatic trail (t_p). The rolling resistance, described in the subsection, is produced by the normal pressure distribution and acts along the lateral axis (M_y). The overturning moment (M_x) is produced due to the normal force lateral shifting (e_y) due to the camber and sideslip angle. Two different approaches for the overturning moment definition for motorcycle tires are shown in Figure 4.4b. In the tire contact point C' , defined as the intersection between the wheel plane and the road plane, M_x is produced by the camber arm (b) and the lateral deflection not shown in the figure. While for the point C , the overturning moment is produced only by the lateral deflection, which is low for a motorcycle and can be neglected [171].

Figure 4.4a shows the forces acting on the tire contact patch with the ground, and their relative distance from the center point. The tire moments along the x for the point C can be modeled as follows [171]:

$$M_x^C = (q_{x1} + q_{x3} \frac{F_y}{F_z}) F \approx q_{x3} F_y \quad 4.9$$

where q_{x1} is an offset term that can be neglected, and q_{x3} is a term related to the lateral deflection. For a motorcycle tire, the overturning moment is mainly due to the camber effect

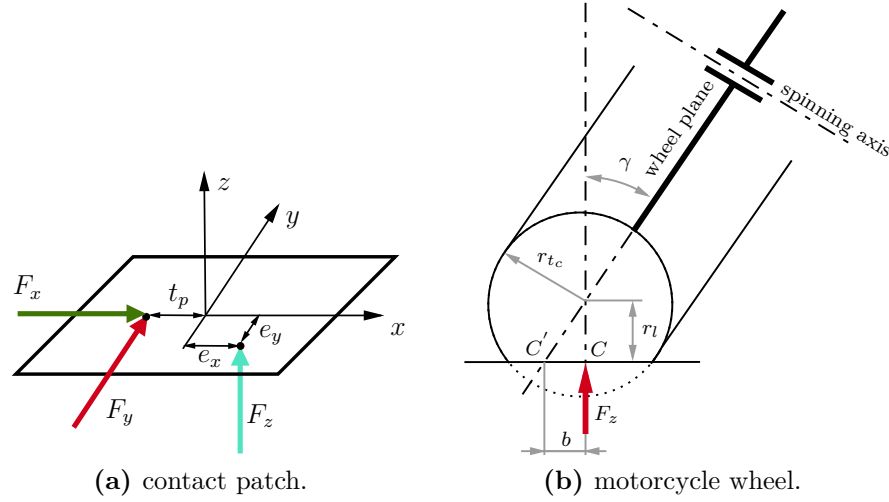


Figure 4.4: **a)** shows the tire patch with the coordinate system. The resultant force does not act on the center, thus, moments are produced about the patch center. **b)** shows the contact patch for a motorcycle wheel, and b is the arm for the overturning moment due to the normal force.

and can be neglected for motorcycles. The vertical moment (M_z) is due to the lateral force, the camber thrust, and the spin slip, and can be defined as follows:

$$M_z = M_{z,\alpha} + M_{z,\gamma} + M_{z,\varphi} \quad 4.10$$

$$M_{z,\alpha} = -t_p F_y \quad 4.11$$

$$M_{z,\gamma} = -k_t F_z \gamma \quad 4.12$$

$$t_p = \frac{1}{3} \sqrt{\frac{F_z}{K_z} \left(2R^2 - \frac{F_z}{K_z} \right)} \left(1 - \frac{k_\alpha}{3\mu} |\tan(\alpha)| \right) \quad 4.13$$

where k_t is the tire normalized scrub stiffness, t_p is the pneumatic trail proportional to the contact patch length, R is the wheel radius, and K_z is the tire vertical stiffness. For low values of sideslip angle (few slip in the last part of the contact patch), the lateral shear stress is mainly linear along the x-axis, so the lateral force distribution assumes a triangular shape, and the pneumatic trail assumes a value equal to a sixth of the contact patch length.

$$M_{z,\gamma} = -k_\gamma F_z \gamma \quad 4.14$$

4.3 Vehicle Dynamics

4.3.1 In-plane motion

The vehicle dynamics in a straight line is described in this section, studying only the longitudinal dynamics. The suspensions are neglected, and the aerodynamic forces are considered applied to the vehicle at the center of gravity instead of the center of pressure. The external forces acting on the vehicle are essentially three: the tire rolling resistance (F_{rr}), the aerodynamic forces (F_{air}), and the weight force parallel to the road due to the road grade (F_{gr}). These two former forces are represented in Figure 4.5. Writing the equation of motion along the X axis, the vertical equilibrium along the Z axis, and the moment equilibrium along the Y axis, results in the following:

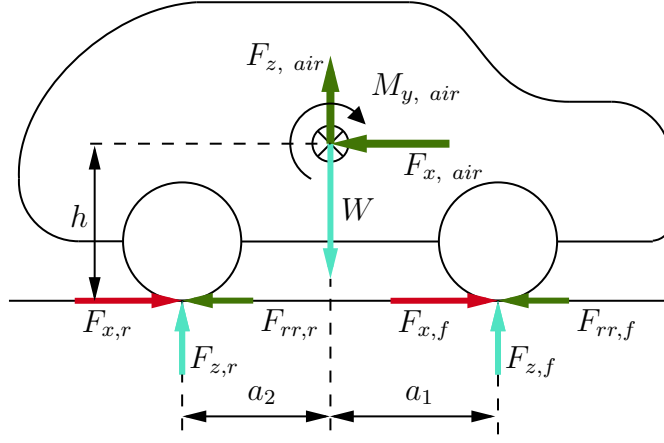


Figure 4.5: Longitudinal forces in plane motion.

$$\sum F_x = m\ddot{x}_G = F_{x,r} + F_{x,f} - F_{x,air} - F_{rr,r} - F_{rr,f} - F_{gr} \quad 4.15$$

$$\sum F_z = m\ddot{z}_G = F_{z,r} + F_{z,f} + F_{z,air} - W \cos(\theta) \quad 4.16$$

$$\sum M_y = I_{yG}\ddot{\mu} = M_{y,air} + F_{z,r}a_2 - F_{z,f}a_1 + F_{rr,f}h + F_{rr,r}h - F_{x,r}h - F_{x,f}h \quad 4.17$$

where m is the vehicle mass, $\ddot{x}_G$ is the center of mass acceleration along x , $\ddot{z}_G$ is the acceleration along z , W is the weight force, h is the center of mass height from the ground, a_1 is the longitudinal distance from the front tire patch contact and the vehicle center of mass, a_2 is the distance between the rear tire contact point to the center of mass, I_{yG} is the vehicle moment of inertia along y , $\ddot{\mu}$ is the pitch acceleration, and $M_{y,air}$ is the moment acting on the vehicle, needed to consider the aerodynamic forces acting on the center of mass. The first subscript indicates the axis direction and the second the nature of the force. Thus, $F_{x,r}$ is the rear tire forces, acting along x . Neglecting the suspension effects, the pitch acceleration ($\ddot{\mu}$) and the vertical acceleration ($\ddot{z}_G$) can be assumed equal to zero. The resolving equation under these hypotheses, the tractive forces, and the vertical forces result as follows:

$$F_x = F_{x,r} + F_{x,f} = m\ddot{x}_G + F_{rr,r} + F_{rr,f} + F_{x,air} + F_{gr} \quad 4.18$$

$$F_{z,r} = \frac{a_1}{w_b}(W \cos(\theta) - F_{z,air}) - \frac{M_{y,air}}{w_b} + \frac{h}{w_b}(m\ddot{x}_G + F_{x,air} + F_{gr}) \quad 4.19$$

$$F_{z,f} = \frac{a_2}{w_b}(W \cos(\theta) - F_{z,air}) + \frac{M_{y,air}}{w_b} - \frac{h}{w_b}(m\ddot{x}_G + F_{x,air} + F_{gr}) \quad 4.20$$

$$W = mg \quad 4.21$$

$$F_{gr} = W \sin \theta \quad 4.22$$

$$F_{rr,r} = F_{z,r} \cdot c_{rr,r} \quad 4.23$$

$$F_{rr,f} = F_{z,f} \cdot c_{rr,f} \quad 4.24$$

$$w_b = a_1 + a_2 \quad 4.25$$

where w_b is the wheelbase, θ is the road slope, h is the center of gravity from the ground, $c_{rr,f}$ and $c_{rr,r}$ are the front and rear rolling resistance coefficients. These two latter coefficients are considered constant and equal, so that they will be just substituted by c_{rr} in further equations. Under acceleration, a fraction of the propulsive power is spent to accelerate

rotating masses like the front and rear wheels, the chain, gearbox, and motor. To account for the rotational inertia, the equivalent mass [240] is described as follows:

$$m_{\text{eq}} = m + \frac{I_{\text{w}}^{\text{f}}}{r_{\text{w}}^{\text{f}^2}} + \frac{I_{\text{w}}^{\text{r}} + m_{\text{c}} + r_{\text{c}}^2}{(1+k)^2 r_{\text{w}}^{\text{r}^2}} \quad 4.26$$

where I_{w}^{f} and I_{w}^{r} are the spin moment of inertia of front and rear wheels respectively, m_{c} and r_{c} are the chain mass and the wheel sprocket, r_{w}^{f} and r_{w}^{r} are the wheel radius, and k is the longitudinal slip. Substituting m_{eq} ¹ in Equation 4.18, the effect of rotational inertia is considered, which can account for an additional 5% to 8% of the mass [240]. To calculate the equivalent mass is needed to know the moments of inertia of all the rotating components or estimate them by empirical equations [73]. Because of the unknown values of rotating mass, the contribution of equivalent mass to vehicle dynamics was neglected.

The aerodynamic force is generated by the air encountered during the vehicle's motion, and results from two factors: the shape drag and the skin friction [73]. The shape drag is due to the difference in pressure between the vehicle's front (high pressure) and rear (low pressure), and the shear stress resulting from the friction between the air close to the vehicle's skin and the air away from the vehicle. The air flows outside the vehicle and through the vehicle for cooling or heating. Between these two forms, the former is dominant, accounting for more than 90% of the total resistance of passenger cars [306]. The aerodynamic resistance can be described by three forces and three moments acting on the center of gravity, and for motorcycles, the most important components are the drag and lift forces [50]. The three moments are needed because the center of pressure might not coincide with the center of gravity. The center of pressure is the point at which the aerodynamic forces do not generate moments, and it is generally located above the center of mass [50], resulting in a tendency of steering into the lean during cornering if not balanced by the rider [89]. The following equations are usually used to describe the aerodynamic forces [73, 111, 132, 171, 227]

$$F_{\text{x,air}} = \frac{1}{2} \rho A_{\text{f}} C_{\text{D}} (v - v_{\text{w}})^2 \quad 4.27$$

$$F_{\text{z,air}} = \frac{1}{2} \rho A_{\text{f}} C_{\text{L}} (v - v_{\text{w}})^2 \quad 4.28$$

$$M_{\text{y,air}} = \frac{1}{2} \rho A_{\text{f}} C_{\text{M}} w_{\text{b}} (v - v_{\text{w}})^2 \quad 4.29$$

where ρ is the air density, A_{f} is the front cross section area, v_{w} is the wind speed, C_{D} is the drag coefficient, C_{L} is the lift coefficient, and C_{M} is the pitch coefficient. The latter coefficients can be estimated from experimental wind tunnel testing or computational fluid dynamics simulation. The three coefficients are a function of the speed, the angle of relative wind, which changes significantly with rider positioning [305], crosswind [53], and during cornering [287]. During high-speed cornering, the rider leans into the turn, increasing the frontal area and increasing the drag coefficient. For a 45° lean, the drag coefficient increased by 8.2% and the lift coefficient by 111.1% compared to the straight line case [287]. In this work, the drag, lift, and pitch coefficients are considered constant, as is usually done in other works.

4.3.2 Lateral dynamic

The vehicle was modeled as a linear single-track or two-axle model for four-wheel vehicles and as a bicycle model for motorcycles. Figure 4.6 shows the kinematic and dynamic cornering for the single-track vehicle.

¹this substitution is needed if the tractive forces are written as a function of the motor torque. Otherwise, are the forces exchanged between the road and the tire so the rotating masses are not involved.

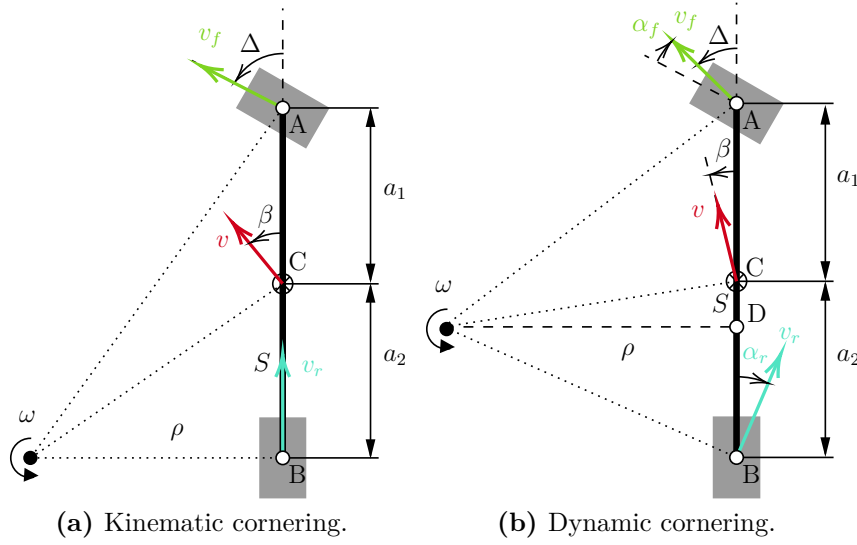


Figure 4.6: a) shows the kinematic cornering for a track vehicle model; b) shows the cornering while considering the dynamic effects. The alphas are the tire sideslip angle, while β is the vehicle sideslip angle. Δ is the steering angle; here was exaggerated for illustrative reasons.

The suspension, aerodynamic drag, and rolling resistance effects were neglected, and the equation of motion was written along the x, y, and z axes, balancing the forces and the moment as follows:

$$\sum F_x = m\ddot{X}_G = -F_{y,f} \sin(\Delta_f) + F_{x,f} \cos(\Delta_f) - F_{y,r} + F_{x,r} \cos(\Delta_r) \quad 4.30$$

$$\sum F_y = m\ddot{Y}_G = F_{y,f} \cos(\Delta_f) + F_{x,f} \sin(\Delta_f) + F_{x,r} \cos(\Delta_r) + F_{y,r} \sin(\Delta_r) \quad 4.31$$

$$\sum M_z = I_z \dot{r} = M_{z,f} + M_{z,r} + a_1(F_{y,f} \cos(\Delta_f) + F_{x,f} \sin(\Delta_f)) - a_2(F_{y,r} \cos(\Delta_r) + F_{x,r} \sin(\Delta_r)) \quad 4.32$$

where Δ_f is the front steering angle, Δ_r is the rear steering angle, and I_z is the moment of inertia or yaw moment inertia. Investigating the steady-state conditions and neglecting the external forces as the aerodynamic drag and the tire rolling resistance, the equations 4.30, 4.31, and 4.32 are simplified as follows:

$$\sum F_x = -\dot{x}^2 \rho \beta \quad 4.33$$

$$\sum F_y = \dot{x}^2 \rho \quad 4.34$$

$$\sum M_z = 0 \quad 4.35$$

where ρ is the turn curvature, and β is the vehicle sideslip angle.

Even neglecting the longitudinal resistance forces, a longitudinal force must be supplied to maintain the steady-state condition as suggested by equation 4.33. This latter force could be provided by the lateral tire force in the case of kinematic cornering, while sideslip angles are present, a driving force is needed. The contribution of the lateral force along the x-axis is called induced drag, due to the analogy with induced drag in a wing with an angle of attack different from zero. Finally, the equilibrium along the x-axis was described by a simple model for motorcycles as follows:

$$\sum M_x = 0 \rightarrow m\ddot{y}_G \cos(\gamma) = M_{x,f} + M_{x,r} + F_y \sin(\gamma) \quad 4.36$$

Neglecting the overturning moments results in the following:

$$\tan(\gamma) = -\frac{m\ddot{y}_G}{mg} = \frac{\ddot{y}_G}{g} \quad 4.37$$

The lateral dynamic model is suitable for cars and motorcycles, considering or not equation 4.37.

4.4 Vehicle power, energy, and losses

4.4.1 Vehicle power and energy demand

The vehicle energy consumption is due to the mechanical resistance and the auxiliary power. This latter power is needed to supply all the systems that are not involved directly in the riding, like the stereo, A/C system, etc. For motorcycles, the auxiliary power is low due to the vehicle's missing of complex auxiliary systems or at least as a first approximation. From the previous sections, the traction to the wheel needed during the ride is as follows:

$$F_{\text{trac}} = F_{\text{rr}} + F_{\text{inertia}} + F_{\text{grade}} + F_{\text{air}} \quad 4.38$$

where F_{trac} is the tractive or propulsive force at the wheel, F_{rr} is the force due to the tire rolling resistance, F_{inertia} is the force due to the inertia, F_{grade} is the force given by the road slope resistance, and F_{air} is the force due to the aerodynamic resistance. The power at the wheel can be expressed as the product of the force and the vehicle speed, assuming a null tire slip velocity as follows:

$$P_w = F_{\text{trac}} \cdot v \quad 4.39$$

Energy can be obtained by integrating the power at the wheel over time, resulting in the following:

$$E = \int_0^t P_w d\tau \quad 4.40$$

Normalizing the energy by the distance traveled as in equation 4.41, the mean tractive force or specific energy ($\bar{E}$) is obtained.

$$\bar{E} = \frac{E}{\text{distance}} \quad 4.41$$

By first substituting equation 4.38 into 4.39, and then incorporating it into 4.41, the resulting derivation proceeds as follows:

$$\bar{E} = \frac{\int_0^t mgc_{\text{rr}} \cos(\theta) v d\tau}{\int_0^t v d\tau} + \frac{\int_0^t m a v d\tau}{\int_0^t v d\tau} + \frac{\int_0^t mg \sin(\theta) v d\tau}{\int_0^t v d\tau} + \frac{\int_0^t \frac{1}{2} \rho A_f C_D v^3 d\tau}{\int_0^t v d\tau} \quad 4.42$$

Considering a null road grade, and a constant vehicle speed equation 4.42 simplifying in this manner:

$$\bar{E} = mgc_{\text{rr}} + \frac{1}{2} \rho A_f C_D v^2 \quad 4.43$$

Thus, there is an independent speed term due to the rolling resistance, and a speed quadratic term due to the air resistance. Then the power to the wheel will be equal to the power to the motor or engine plus the losses, the same for the battery power as the motor power. The auxiliary power was considered speed and load independent, thus it is a constant term

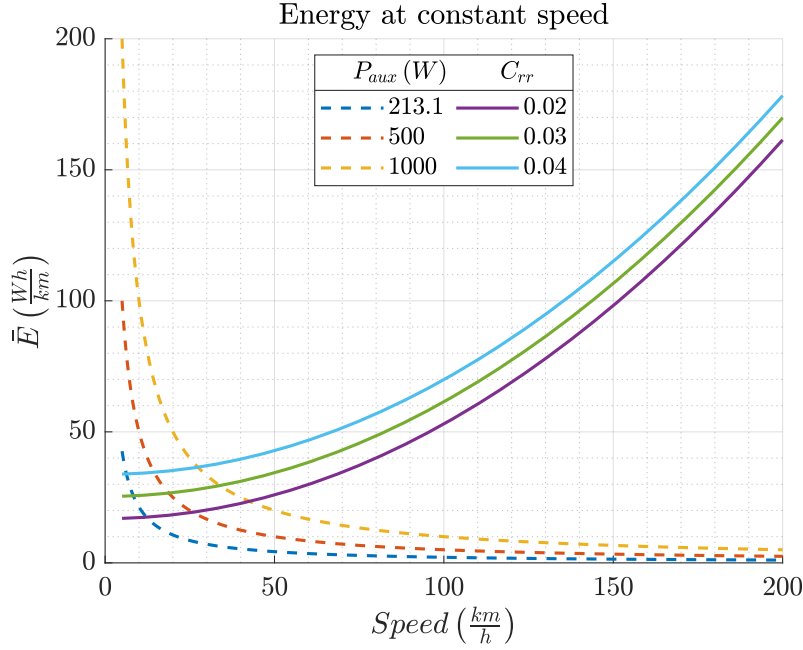


Figure 4.7: Normalized energy by the distance for constant speed. The energy distance is the sum of the auxiliary curve (dashed lines) and the vehicle resistance (continuous lines).

leading to a specific energy which tends to zero when speed tends to infinity, as described in equation 4.44 for a constant vehicle driving speed.

$$\bar{E}_{aux} = \frac{\int_0^t P_{aux} d\tau}{\int_0^t v d\tau} = \frac{P_{aux}}{v} \quad 4.44$$

The total specific energy is given by adding the terms due to the vehicle resistance and the auxiliary power as follows:

$$\bar{E}_{tot} = \bar{E} + \bar{E}_{aux} \quad 4.45$$

Figure 4.7 shows the example of the specific energy for three different rolling resistance coefficients and three auxiliary powers. The optimal speed consumption for constant speed riding is determined by posing the specific energy first derivative equal to zero as follows:

$$v^* = \sqrt[3]{\frac{P_{aux}}{\rho C_d A_f}} \quad 4.46$$

4.4.2 Tire slip losses

Tires dissipate energy during their rolling. This latter energy was described as the mechanical energy dissipated into heat for a unit distance of a rolling tire [261]. The first law of thermodynamics can describe the resistance force to the rolling of a closed system [101], as follows:

$$\dot{W} + \dot{Q} = \dot{E} \quad 4.47$$

The total energy rate is equal to the power and the heat transferred to the system. A tire had a total energy equal to the sum of the internal (U), kinetic (K), and potential energies (V). To be coherent with the meaning of rolling resistance, it can be described as the changes

in the thermal energy of the tire, as follows:

$$F_r v = \left(\frac{dU}{dt} - \dot{Q} \right) = \left(\dot{W} - \frac{dK}{dt} - \frac{dV}{dt} \right) \quad 4.48$$

It is important to stress that here the resistance force is the equivalent of the opposing force to the rolling, but it is not the real cause of the resistance. In the steady state condition, the equation 4.48 results in the following equation:

$$F_r = \frac{\dot{W}}{v} = \frac{P_{in} - P_{out}}{v} \quad 4.49$$

Thus, the rolling resistance is equal to the difference between the tire input (driven or braking torque) and output power (force transmitted to the ground). The torque needed to drive the vehicle can be obtained by tire equilibrium moment along the y-axis:

$$T = I_w \dot{\omega}_y + \sum M_y \quad 4.50$$

Finally, the input power to the wheel and the output power were described in equations 4.51 and 4.52, respectively.

$$P_{in} = T \omega_y \quad 4.51$$

$$P_{out} = F v_x \quad 4.52$$

The output power is the dot product of the force exchange with the ground and the tire speed. In the next subsections will be introduced the description of the power slip loss in steady-state conditions.

4.4.3 Longitudinal power slip loss

The vertical distribution of the contact pressure is affected by the velocity. An increment of the speed results in a more forward vertical pressure distribution. The moment given by the vertical force resultant is commonly called rolling resistance. The ratio between the distance along the x-axis and the loaded radius is called the rolling resistance coefficient. In a steady state condition, in pure longitudinal dynamics (i.e., no camber and no sideslip), the rolling resistance can be obtained by equation 4.49 as follows:

$$F_r = T \frac{\omega_y}{v_x} - F_x \quad 4.53$$

subsisting equation 4.50 in the previous equation results:

$$F_r = \omega \sum M_y - F_x v_x = (F_z e_x + F_x R_l) \frac{\omega_y}{v_x} - F_x \quad 4.54$$

Assuming a small quantity of longitudinal slip, the longitudinal force can be expressed as a linear function of the slip, and by definition of slip, the equation 4.55 becomes:

$$F_r = (F_z e_x + C_k k R_l) \frac{(1 + k)}{R_e} - C_k k \quad 4.55$$

After manipulation and using the definition of the rolling resistance $c_{rr} = e_x / R_l$ the equation 4.55 become:

$$F_r = C_k k \left(k \frac{R_l}{R_e} + \frac{R_l}{R_e} - 1 \right) + F_z c_{rr} \frac{R_l}{R_e} (1 + k) \quad 4.56$$

The power loss can be obtained by multiplying equation 4.56 by the speed. Dividing the resistance force by the vertical force acting on the wheel axle results in the extended rolling resistance coefficient:

$$f = c_{rr} \frac{R_l}{R_e} (1 + k) + c_k k^2 \frac{R_l}{R_e} + c_k k \left(\frac{R_l}{R_e} - 1 \right) \quad 4.57$$

where the term c_k was the normalized longitudinal tire stiffness. Usually, the loaded radius is smaller than the effective radius, thus the last term on the right-hand side is negative. The equilibrium along the x-axis and the load transfer were described in the following equations:

$$F_x = C_k k = \frac{1}{2} \rho_{air} C_x A v_x^2 + m \ddot{x}_G + F_z c_{rr} \quad 4.58$$

$$F_{z,r,f} = F_{z,r0,f0} \mp \frac{M_{y,air}}{l} \pm m \ddot{x}_G \frac{h}{l} \pm F_{x,aer} \frac{h}{l} \quad 4.59$$

where the simplified equation for the steady state can be obtained by imposing $\ddot{x}_G$ equals zero. The equations can be simplified further by neglecting the aerodynamic effects. Resolving the equations for a given speed gave the extended rolling resistance coefficient. The formula introduced in equation 4.57 was applied to a sports motorcycle. This latter motorcycle corresponds to the Sports Big model on BikeSim. The latter is a multi-body software used for high-fidelity motorcycle dynamics simulation.

The simulation data from the multi-body vehicle model was compared with two slip loss models: a simple model and an aerodynamics model. The former does not consider the aerodynamic load transfer and lift, the latter model also considers these effects. Determining the aerodynamic coefficients requires CFD simulation or experimental test, which are not always easy to perform; thus, if the influence on consumption is low may be neglected. The vehicle was slowly accelerated (0.05 m/s^2) from a speed of 3.6 to 300 km/h, and the results are shown in Figure 4.8.

The highest power loss value was 300 km/h, and there was a local maximum around 110 km/h. The simple model and the aerodynamic model will well represent the reference loss until 140 and 220 km/h, respectively. The driving torque was practically identical to the reference for both models, figure 4.8c, because the driving torque is mainly due to the longitudinal aerodynamic force. For high-speed values, the simple model overestimates the longitudinal slip, while the other model slightly underestimates, Figure 4.8d. The extended rolling resistance or longitudinal slip resistance is shown in Figure 4.8b, which is very low if compared to the rolling resistance, or at least it is for this tire. Although the error margin is significant at elevated vehicle speeds, the power slip at these velocities remains minimal, as depicted in Figure 4.8a, measuring in the range of hundreds of watts, whereas the aerodynamic power is measured in the range of kilowatts. Thus, in first approximation, the power losses due to the longitudinal slip could be modeled considering zero aerodynamic moments, or neglected altogether, due to the low impact on the power loss.

4.4.4 Cornering resistance

In cornering, lateral forces are supplied by the tire. These latter forces allow the vehicle to maintain its trajectory but also act as an opposing force to the longitudinal movement. The planar vehicle dynamics can be described as follows:

Assuming a constant forward speed ($\ddot{x} = 0$) and the steady state condition ($\dot{r} = 0$), the roll angle can be obtained by the vertical equilibrium, neglecting the rider lean angle and the tire width, as follows:

$$\tan(\gamma) = -\frac{\ddot{y}_G}{g}$$

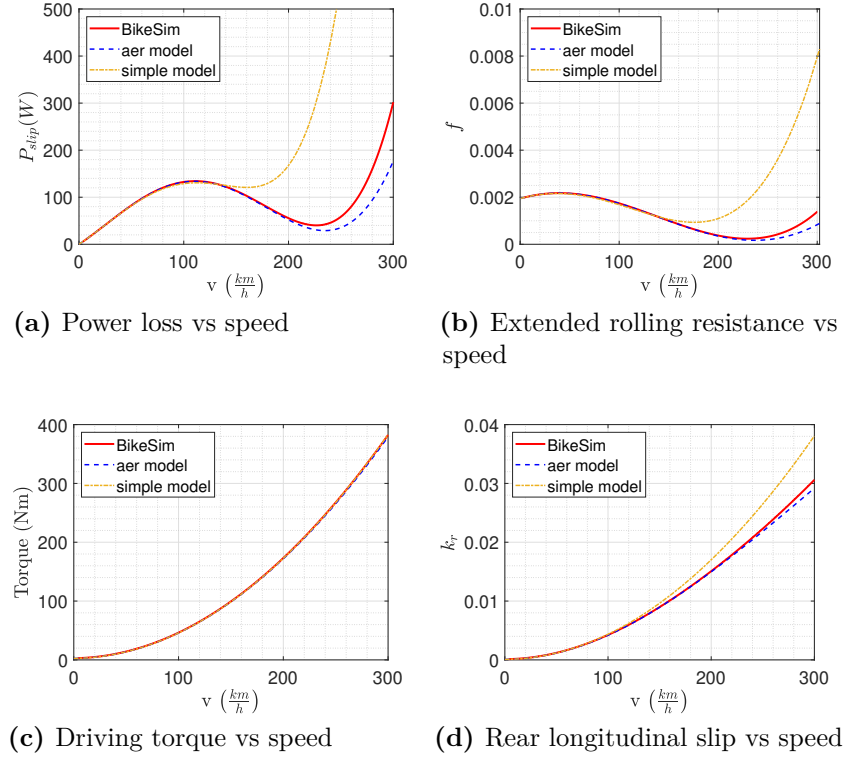


Figure 4.8: Shows the comparison between the two models and the reference model (BikeSim). The aerodynamics model (blue dashed line) takes into account the aerodynamic effect. The simple model (yellow dotted line) does not consider the aerodynamic moments and the lift force.

Resolving the equations, with the hypothesis of small sideslip angles, it was possible to obtain the driving force needed for the traction due to the lateral dynamics as follows:

$$F_D = F_{x,f} + F_{x,r} \quad 4.60$$

$$F_{x,f} = \sigma F_D \quad 4.61$$

$$F_D = \frac{M + T_y}{D} \quad 4.62$$

$$M = 2 \sin(\Delta_f - \Delta_r)(M_{z,f} + M_{z,r}) \quad 4.63$$

$$T_y = v_x^2 m \rho (a_1 \sin(\beta + \Delta_f - \Delta_r) + a_2 \sin(\beta - \Delta_f + \Delta_r) - w_b \sin(-\beta + \Delta_f + \Delta_r)) \quad 4.64$$

$$D = 2w_b(\cos(\Delta_f) - \sigma \cos(\Delta_f) + \sigma \cos(\Delta_r)) \quad 4.65$$

where β is the vehicle sideslip angle, σ is the longitudinal driving bias, ranging from zero to one. When σ is equal to zero, the traction is only due to the rear wheel, and when equal to one, the traction is only due to the front wheel. For a front steering vehicle and rear traction vehicle, such as motorcycles, the equation 4.62 is simplified as follows:

$$F_D = -\frac{(M_{z,f} + M_{z,r})\Delta_f}{w_b} + (\beta_K - \beta)m\ddot{y}_G \quad 4.66$$

The subscript K stands for kinematic (Ackerman condition). The first term on the right side was the contribution due to the moments on the z-axis of the front and rear tires. The difference between the kinematic and the vehicle sideslip angle is equal to the difference between the front and rear sideslip angles. The tire moment along the z-axis can be described

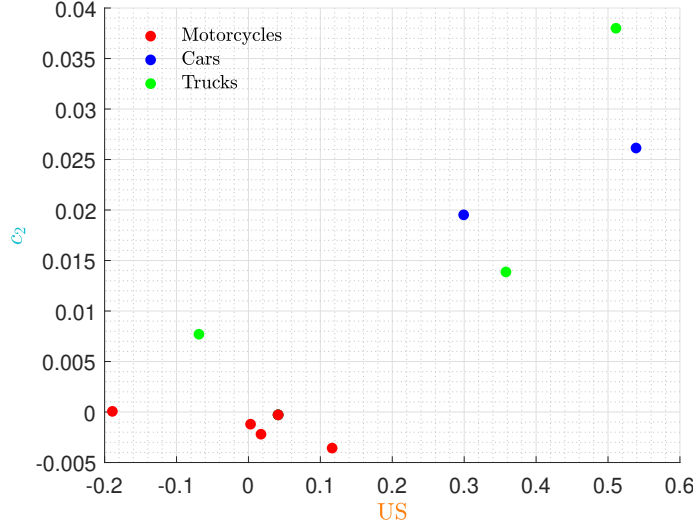


Figure 4.9: Shows the values of the cornering driving force coefficient (c_2) and the understeer coefficient (US) for different families of vehicles.

as a function of the tire camber, sideslip angle, and lateral acceleration under the hypothesis of small sideslip angle.

$$M_{z,f} \approx \left[\frac{1}{3} \sqrt{\frac{a_2 mg}{w_b K_{z,f}}} (2r_w^f - \frac{a_2 mg}{K_{z,f}}) \left(1 - \frac{|(c_{\gamma,f} - 1)\ddot{y}_G|}{3\mu g} \right) (c_{\gamma,f} - 1) + k_{t,f} \right] \frac{a_2}{l} m \ddot{y}_G \quad 4.67$$

$$M_{z,r} \approx \left[\frac{1}{3} \sqrt{\frac{a_1 mg}{w_b K_{z,r}}} (2r_w^r - \frac{a_1 mg}{K_{z,r}}) \left(1 - \frac{|(c_{\gamma,r} - 1)\ddot{y}_G|}{3\mu g} \right) (c_{\gamma,r} - 1) + k_{t,r} \right] \frac{a_1}{w_b} m \ddot{y}_G \quad 4.68$$

Finally, the resultant longitudinal force provided by the tire can be expressed in a polynomial form with the lateral acceleration:

$$F_D = -C_{y,1} \ddot{y}_G + C_{y,2} \ddot{y}_G^2 \quad 4.69$$

where the coefficients are constant for the entire manoeuvre and $C_{y,1}$ is always positive. The coefficients $C_{y,2}$ can be negative for the motorcycles. The driving force is null in the case of zero lateral acceleration (trivial case). The understeer coefficient (US) is a parameter used to describe the vehicle behavior in cornering, and neglecting the tire moments can be defined as follows:

$$US = \frac{\alpha_r - \alpha_f}{\ddot{y}_G} \quad 4.70$$

The understeer coefficient may be null for a neutral vehicle, but in this case, the driving force due to the lateral acceleration is not null. The condition to have a null driving-induced drag is to obtain a kinematic cornering condition. Noteworthy is the possibility of having a negative driving force (braking) when the sideslip angle is negative, which is often reported in the case of motorcycles. This latter effect has consequences on the conservative and energy aspect which will be discussed further. In BikeSim, the Big sport motorcycle model followed a path with a fixed curvature radius while the motorcycle speed was gradually increased to explore all the camber angles. Results are shown in Figure 4.10. The rear cornering wheel is always negative, while the front at a roll angle of 29° changes sign due to the negative sideslip angle. The cornering power was normalized by the driving power, excluding the engine and driveline efficiencies.

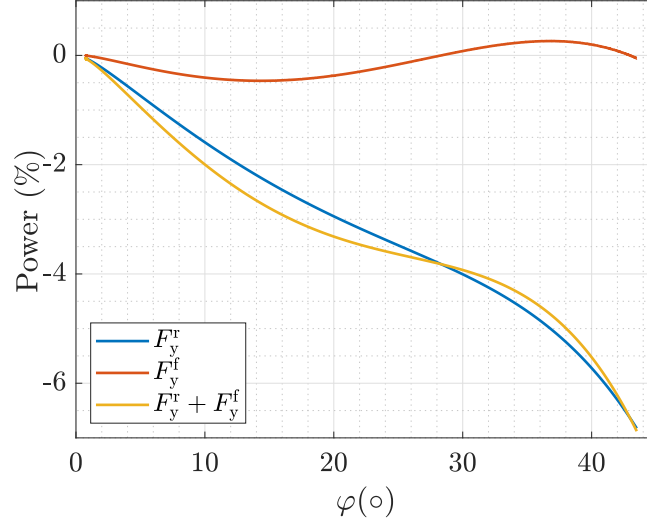


Figure 4.10: Shows the ratio between the cornering resistance and the total resistance power, for the wheel rear cornering power (blue line), the wheel front cornering power (red line), and their sum (yellow line).

The cornering power ranges from 0 to -6.9% of the total resistance power, and the trend can be approximated with a linear relationship on the roll angle. Due to the slow acceleration, the simulation can be considered in steady-state conditions. The rear wheel generates more resistance than the front wheel, because of the lower stiffness tire and thus the higher sideslip angle. Classic approval driving cycles do not consider road slopes and lateral dynamics. There is an important aspect of the model for the cornering power, which is not conservative. Indeed, assuming zero resistance from the other aspects, given the possibility of a negative sideslip angle results in a positive cornering resistance, which, of course, is not possible. From the linear model for the joint lateral force and camber thrust described in equation 4.8, if the camber stiffness is greater than one, the sideslip angle is negative [50]. In conclusion, the cornering power was described analytically and numerically with a dedicated simulation on a multi-body software. This latter power is not the principal reason for vehicle resistance, but it is significant (6.8%) at high lateral acceleration or roll angle. Considering the road riding, with lower roll angles than track riding, the cornering power will be neglected due to its low influence on consumption.

4.5 Motorcycle Riding Range Law

The energy consumption for electric vehicles can be described by a linear or logarithmic relationship with the vehicle and rider masses as follows [301, 302]:

$$\bar{E} = \alpha + \beta m \quad 4.71a$$

$$\log(\bar{E}) = \alpha' + \beta' \log(m) \quad 4.71b$$

where m is the vehicle and rider mass, α , β , α' , and β' are constants determinate by fitting data. The riding range (RR) is calculated as the ratio between the battery capacity and the energy consumption as follows:

$$RR = \frac{C_{b,\max}}{\bar{E}} \quad 4.72$$

where RR is the riding range in km, and $C_{b,\max}$ is the maximum battery capacity. Furthermore, the vehicle mass is described via the maximum battery capacity, by Equation 2.6.

Substituting Equations 2.6 and 4.71a in Equation 4.72 provides important information on the riding range as a function of the mass as described in the following:

$$RR = \frac{C_{b,\max}}{\alpha + \beta m} = \frac{C_{b,\max}}{\alpha + \beta(a_b^* C_{b,\max} + b_b^*)} \quad 4.73$$

where a_b^* and b_b^* are the identified parameters modified to include a 70 kg rider on the overall mass. Similarly, the riding range can be described with the logarithmic energy consumption by Equation 4.71b, resulting:

$$RR_{\log} = \frac{C_{b,\max}}{e^{\alpha'} \beta' m} = \frac{C_{b,\max}}{e^{\alpha'} \beta' (a_b^* C_{b,\max} + b_b^*)} \quad 4.74$$

Figure 4.11 illustrates the riding range for the two models, depicted as a function of vehicle mass and rider (Overall mass). A null riding range (RR) indicates a null battery size, and as the vehicle mass increases due to the battery size, the riding range progressively increases. Subsequently, as the battery capacity approaches infinity, the riding range asymptotically stabilizes at a constant value; indeed the limit results as follows:

$$\lim_{C_{b,\max} \rightarrow \infty} RR = \lim_{C_{b,\max} \rightarrow \infty} \frac{C_{b,\max}}{\alpha + \beta(a_b^* C_{b,\max} + b_b^*)} = \frac{1}{\beta a_b^*} \quad 4.75$$

and is similar to the logarithmic model, converging at a constant value as described in Equation 4.76 for a battery size approaching infinity.

$$\lim_{C_{b,\max} \rightarrow \infty} RR_{\log} = \lim_{C_{b,\max} \rightarrow \infty} \frac{C_{b,\max}}{e^{\alpha'} \beta' (a_b^* C_{b,\max} + b_b^*)} = \frac{1}{e^{\alpha'} \beta' a_b^*} \quad 4.76$$

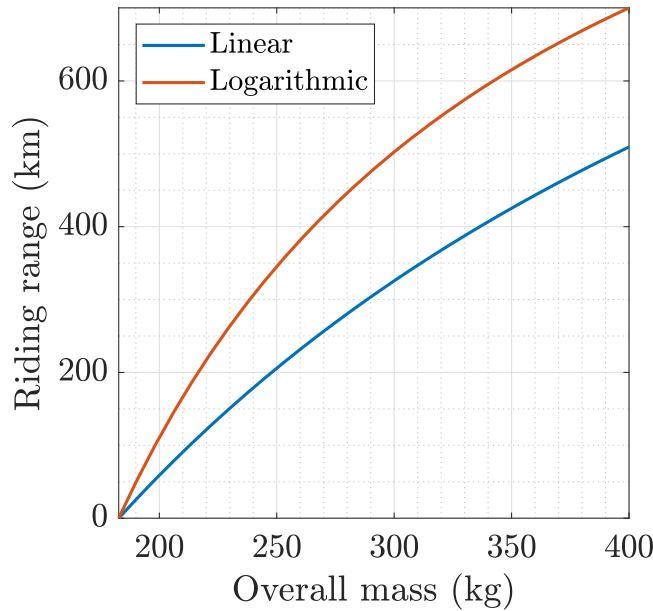


Figure 4.11: Shows the riding range as a function of the overall mass (vehicle mass plus 70 kg of rider). The linear model (blue line) predicts a lower value of the riding range than the logarithmic model (orange line). Both models start from a null battery capacity, meaning a null riding range.

The consumption models are based on different kinds of road vehicles, like cars, bicycles, trucks, and powered two wheeler vehicles, nonetheless, the model remains valid as a comprehension of the riding range problem. Thus, the riding range values might not precisely

predict the motorcycle's riding range but represent the right behavior. The battery sensitivity on the riding range was investigated. For the linear models, the riding range sensitivity to the battery capacity (S_b^{RR}) can be derived by Equations 2.6 and 2.7, resulting as described in Equation 4.77.

$$S_b^{RR} = \frac{\partial RR}{\partial C_{b,\max}} \frac{C_{b,\max}}{RR} = \frac{\alpha + \beta b_b^*}{\alpha + \beta b_{b,\max}^* + \beta a_b^* C_{b,\max}} \quad 4.77$$

Similar the sensitivity for the logarithmic model ($S_b^{RR_{\log}}$) was derived as follows:

$$S_b^{RR_{\log}} = \frac{\partial RR_{\log}}{\partial C_{b,\max}} \frac{C_{b,\max}}{RR_{\log}} = \frac{b}{a_b^* C_{b,\max} + b_{b,\max}^*} \quad 4.78$$

Figure 4.12 shows the S_b^{RR} and $S_b^{RR_{\log}}$ functions against the battery capacity. The sensitivity is equal to one for a zero battery capacity, which corresponds to a zero riding range, and a variation of the battery capacity completely influences the riding range. While for a bigger and bigger battery capacity, both the sensitivity indicators tend to zero, indeed, an increment of the battery results in an increment of the consumption tending to the asymptotical value described in Equations 4.75, 4.76. The sensitivity has high values between the 5 kWh and the 20 kWh maximum battery capacity, which is a typical range of the motorcycle battery size. Thus, the right battery sizing is crucial for the vehicle mass, riding range, and energy consumption. Finally, it is important to stress that the energy consumption models are

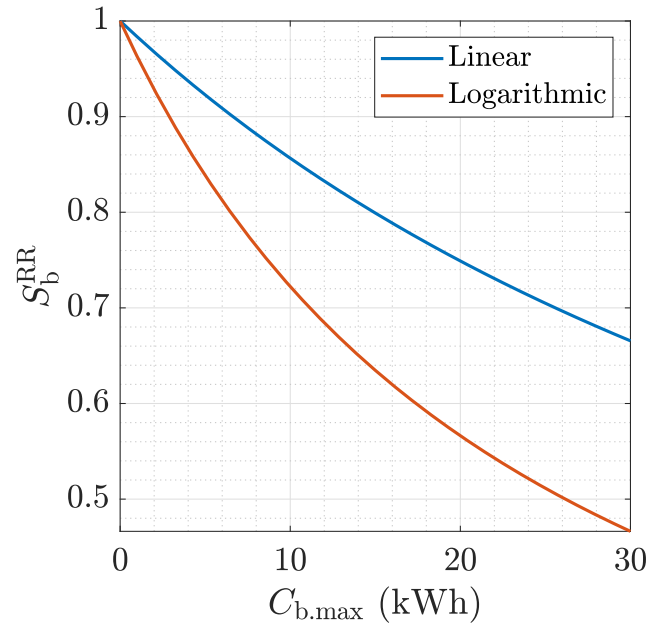


Figure 4.12: Shows the battery sensitivity analysis on riding range vs the battery maximum capacity for the linear energy consumption model (blue line) and the logarithmic model (orange line).

based on linear regression of different types of road vehicles, thus, the identified parameters might not fit accurately the motorcycle consumption only. Nevertheless, the method applied could be used on more accurate data and still provided significant hints on the riding range. Furthermore, the high sensitivity value across the typical motorcycle battery size highlights the high influence of the battery on the riding range

4.6 Vehicle and Braking Performance

Vehicle performance and drivability are crucial aspects of the vehicle design. Top speed, gradeability or gradability, and acceleration time are common quantifiers for vehicle performance on passenger cars [114]. The top speed or maximum cruising speed is the limit speed at which the vehicle is no longer capable of acceleration on a flat road. Gradeability is the ability to drive uphill at a minimum speed ($v_{\min}$), and it is relevant for heavy-duty vehicles with high payload. The acceleration time is the time needed to accelerate the vehicle from 0 to a final speed (v_f), with common values being 60 mph and 100 km/h. The top speed or maximum speed can be obtained from the equilibrium along the X-axis between the driving force described in Equation 4.60 and the resistance forces as follows:

$$F_D = mgc_{rr} \cos(\theta) + mg \sin(\theta) + \frac{1}{2} \rho A_f C_D v_t^2 \quad 4.79$$

and assuming θ is equal to zero, the formula holds for flat roads. resolving for v_t , the maximum speed resulting:

$$v_t = \sqrt{\frac{F_D}{mgc_{rr} + \frac{1}{2} \rho A_f C_D}} \quad 4.80$$

The maximum might determine the maximum speed of the vehicle speed of the power plant, depending on the maximum motor speed and gear ratio as described in Equation 4.81:

$$v_t = \frac{\pi \omega_{\max} r_w^f}{30\tau} \quad 4.81$$

where $\omega_{\max}$ is the maximum motor speed in rpm, and τ is the total gear ratio between the motor and the wheel. The power needed to reach the maximum speed follows from Equation 4.79 by multiplying each term for the top speed, resulting as follows:

$$P_{\max} = (F_D)v_t = mgc_{rr}v_t + \frac{1}{2} \rho A_f C_D v_t^3 \quad 4.82$$

The vehicle is expected to move forward very slowly when climbing a steep slope, thus, the contribution of the aerodynamic forces can be neglected, and the vehicle is not accelerating. Under these latter hypotheses, the maximum gradability can be written as:

$$F_D = mgc_{rr} \cos(\theta^*) + mg \sin(\theta^*) \quad 4.83$$

where θ^* is the maximum road angle, and the power needed to maintain the minimum design speed ($v_{\min}$) is described in Equation 4.84

$$P_{\max} = F_D v_{\min} = (mgc_{rr} \cos(\theta^*) + mg \sin(\theta^*)) v_{\min} \quad 4.84$$

The acceleration time follows from the equation of motion as follows:

$$m \frac{dv}{dt} = F_D - F_{rr} - F_{x,air} \quad 4.85$$

Then, integrating over time leads to:

$$\int_0^{t_a} dt = t_a = \int_0^{v_f} \frac{m}{F_D - F_{rr} - F_{x,air}} dv = \int_0^{v_f} \frac{m}{F_D - mgc_{rr} \cos(\theta) - \frac{1}{2} \rho A_f C_D v^2} dv \quad 4.86$$

where t_a is the acceleration time. The distance traveled can be found starting from 4.85:

$$m \frac{dv}{dt} = m \frac{dv}{dt} \frac{dx}{dx} = m \frac{dv}{dx} v = F_D - F_{rr} - F_{x,air} \quad 4.87$$

Then integration over the distance results:

$$D_a = \int_0^{v_f} \frac{m \cdot v}{F_D - F_{rr} - F_{x,air}} dv = \int_0^{v_f} \frac{m \cdot v}{F_D - mgc_{rr} \cos(\theta) - \frac{1}{2} \rho A_f C_D v^2} dv \quad 4.88$$

where D_a is the distance traveled to reach the final speed v_f . Equations 4.86 and 4.88 are functions of the vehicle speed and the driving force, which depend on the motor torque, gear ratio of the driveline, and wheel radius. Thus, solving these latter two equations analytically might not be possible, so numerical methods might be used.

According to Equation 4.20, the front tire load decreases proportionally to the driving forces. Thus, there is the possibility of having a null vertical force on the front wheel, and if the driving force increases, the front wheel will lift off the ground. This latter condition is called wheelie and can be found from Equation 4.20 imposing a null vertical force as follows:

$$F_{z,f} \geq 0 \Leftrightarrow \frac{h}{l}(m\ddot{x}_G + F_{x,aer}) \leq \frac{a_2}{l}(W - F_{z,air}) + \frac{M_{y,air}}{l} \quad 4.89$$

and neglecting the aerodynamic effects is possible to find the threshold value of acceleration to avoid the wheelie situation, resulting

$$a_w^* = \frac{m\ddot{x}_G}{W} \leq \frac{a_2}{h} \quad 4.90$$

where a_w^* is the acceleration limit. To increase the acceleration performance, the center of mass can be shifted forward, thus increasing a_2 , or lowering the center of mass by reducing h . Another aspect of the acceleration is the adherence limit. The force between the tire and the ground can not be higher than the adherence limit imposed, and the wheel spinning and locking will occur during traction or braking, respectively. The maximum friction force is proportional to the vertical load by the global longitudinal adherence coefficient $\mu_{x,peak}$, which is a function of many variables like the ambient temperature, tire rubber compound, tire aging, humidity, and vertical load [171, 240]. This latter coefficient is defined as the ratio between the peak value of the tire longitudinal force and the corresponding vertical load [110].

$$\mu_{x,peak}(F_z) = \frac{F_{x,max}}{F_z} \quad 4.91$$

The acceleration and braking force can not exceed the adherence limit, and the vertical force can not be negative; the following inequalities avoid this condition.

$$|F_x| \leq \mu_{x,max} F_z \quad 4.92$$

$$F_z \geq 0 \quad 4.93$$

For an all-wheels tractive vehicle the maximum acceleration result so equal to $\mu_{x,max}$ assuming constant and the same adherence coefficient on both the wheels, while for a rear wheel vehicle follows by substituting Equations 4.20 and 4.92 into 4.18 resulting as follows:

$$a_{\mu,r}^* = \frac{m\ddot{x}_G}{W} \leq -\frac{F_{x,air}}{W} - \sin(\theta) + \frac{\mu_{x,max}(a_1 W \cos(\theta) - a_1 F_{z,air} - M_{y,air}) - w_b W c_{rr} \cos(\theta)}{(w_b - h\mu_{x,max})W} \quad 4.94$$

where $a_{\mu,r}^*$ is the acceleration limit due to adherence for a rear-driven motorcycle. Assuming negligible the aerodynamic forces, as well as the rolling resistance, and a null road slope, Equation 4.92 simplifies as follows:

$$a_{\mu,r}^* = \frac{\ddot{x}_G}{g} \leq \frac{a_1 \mu_{x,\max}}{w_b - h \mu_{x,\max}} \quad 4.95$$

Similarly, for the front wheel, the limit due to the adherence is described in the following equations for the complex and simple cases.

$$a_{\mu,f}^* = \frac{m \ddot{x}_G}{W} \leq -\frac{F_{x,\text{air}}}{W} - \sin(\theta) + \frac{\mu_{x,\max}(a_2 W \cos(\theta) - a_2 F_{z,\text{air}} + M_{y,\text{air}}) - w_b W c_{rr} \cos(\theta)}{(w_b + h \mu_{x,\max})W} \quad 4.96$$

$$a_{\mu,f}^* = \frac{\ddot{x}_G}{g} \leq \frac{a_2 \mu_{x,\max}}{w_b + h \mu_{x,\max}} \quad 4.97$$

In a similar fashion, the limit due to the stoppie and adherence can be obtained by the following equations:

$$|a_s^*| = \frac{m \ddot{x}_G}{W} \leq \frac{a_1}{h} \quad 4.98$$

$$|a_{\text{brk},r}^*| = \frac{m |\ddot{x}_G|}{W} \leq \frac{F_{x,\text{air}}}{W} + \sin(\theta) + \frac{\mu_{x,\max}(a_1(W \cos(\theta) - F_{z,\text{air}}) - M_{y,\text{air}}) + w_b W c_{rr} \cos(\theta)}{(w_b + h \mu_{x,\max})W} \quad 4.99$$

$$|a_{\text{brk},f}^*| = \frac{m |\ddot{x}_G|}{W} \leq \frac{F_{x,\text{air}}}{W} + \sin(\theta) + \frac{\mu_{x,\max}(a_2(W \cos(\theta) - F_{z,\text{air}}) + M_{y,\text{air}}) + w_b W c_{rr} \cos(\theta)}{(w_b - h \mu_{x,\max})W} \quad 4.100$$

which simplifies under the previous hypothesis in the two following equations.

$$|a_{\text{brk},r}^*| = \frac{m |\ddot{x}_G|}{W} \leq \frac{a_1 \mu_{x,\max}}{w_b + h \mu_{x,\max}} \quad 4.101$$

$$|a_{\text{brk},f}^*| = \frac{m |\ddot{x}_G|}{W} \leq \frac{a_2 \mu_{x,\max}}{w_b - h \mu_{x,\max}} \quad 4.102$$

The acceleration and braking limits as a function of the longitudinal speed for the rear and front traction are shown in Figure 4.13a and Figure 4.13b, for h equal to 0,573 m, a_1 equal to 0,67 m, and l equal to 1,37 m. The rear adherence curve intersects the wheelie limit for an adherence coefficient equal to 1,21; the stoppie limit intersects the front curve at 1,20.

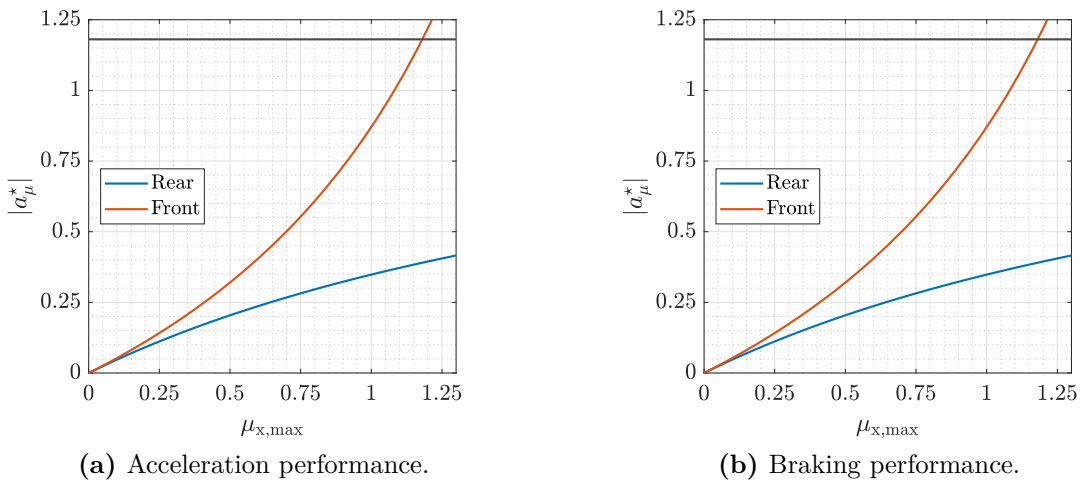


Figure 4.13: Acceleration (on the right) and braking (on the left) performance due to the adherence limit, as a function of the longitudinal slip, on the. The top line on black is the limit due to the wheelie (right plot) and stoppie (left plot).

Considering the same adherence coefficient on both wheels, when they reach the adherence limit contemporaneously, the maximum braking performance is obtained. Other combinations of braking repartition might lead to locking one of the wheels and resulting in a low braking performance. The situation in which the tractive or braking forces are repartitioned to utilize the maximum potential due to adherence on both axles is called ideal [316]. Introducing the longitudinal force as described in Equation 4.92 into Equation 4.18 and resolving for $\ddot{x}_G$, it results as in Equation 4.103.

$$\ddot{x}_G = -\frac{1}{m} (F_{x,f} + F_{x,r} + F_{x,air} + W \sin(\theta) + W c_{rr} \cos(\theta)) \quad 4.103$$

The sum of the rear and front tire forces can be written as follows:

$$F_{x,f} + F_{x,r} = \mu_x F_{z,f} + \mu_x F_{z,r} = \mu_x (W - F_{z,air}) \quad 4.104$$

substituting again Equation 4.92 in the previous equations, and resolving for μ_x follows that:

$$\mu_x = \frac{F_{x,f} + F_{x,r}}{w_b (W \cos \theta - F_{z,air})} \quad 4.105$$

then the difference between the rear and front tire forces results as:

$$F_{x,f} - F_{x,r} = \mu_x F_{z,f} - \mu_x F_{z,r} \quad 4.106$$

Substituting Equations 4.92 and 4.105 into Equation 4.106 result as follows:

$$\begin{aligned} h(F_{x,f}^2 + F_{x,r}^2 + 2F_{x,f}F_{x,r}) + M_{y,air}(F_{x,f} + F_{x,r}) + F_{z,air}(a_1 F_{x,f} - a_2 F_{x,r}) + \\ + W \cos(\theta)(-a_1 F_{x,f} + a_2 F_{x,r}) + hW \cos(\theta)c_{rr}(F_{x,f} + F_{x,r}) = 0 \end{aligned} \quad 4.107$$

Neglecting the aerodynamic effects, the rolling resistance Equation 4.107 simplifies as follows:

$$(F_{x,f} + F_{x,r})^2 + W \cos(\theta)(-\frac{a_1}{h} F_{x,f} + \frac{a_2}{h} F_{x,r}) = 0 \quad 4.108$$

Equation 4.108 describes the relationship between the rear and front tire forces to realize the ideal braking. This latter equation describes a parabola in the $F_{x,r}, F_{x,f}$ plane as shown in Figure 4.14, together with the lines with μ_x constant, and acceleration values. Similarly, the equation for the adherence limit can be found as a function of the rear and front longitudinal forces. Substituting Equations 4.19, 4.103, and 4.105 into 4.92 results as follows:

$$\frac{|F_{x,r}|}{W} \leq \frac{W a_1 \cos(\theta) - F_{z,air} a_1 - M_{y,air} - W h c_{rr} \cos(\theta) - |F_{x,f}| h}{W(w_b + h \mu_x)} \mu_x \quad 4.109$$

in the same fashion, the adherence limit for the front axle can be found in Equation 4.110,

$$\frac{|F_{x,f}|}{W} \leq \frac{W a_2 \cos(\theta) - F_{z,air} a_2 + M_{y,air} + W h c_{rr} \cos(\theta) + |F_{x,r}| h}{W(w_b - h \mu_x)} \mu_x \quad 4.110$$

and neglecting the aerodynamic effects, the rolling resistance on the flat ground, Equations 4.109 and 4.110 simplify as the two following equations respectively.

$$\frac{F_{x,r}}{W} \leq \frac{a_1 - h \frac{F_{x,f}}{W}}{w_b + h \mu_x} \mu_x \quad 4.111$$

$$\frac{F_{x,f}}{W} \leq \frac{a_2 + h \frac{F_{x,r}}{W}}{w_b - h \mu_x} \mu_x \quad 4.112$$

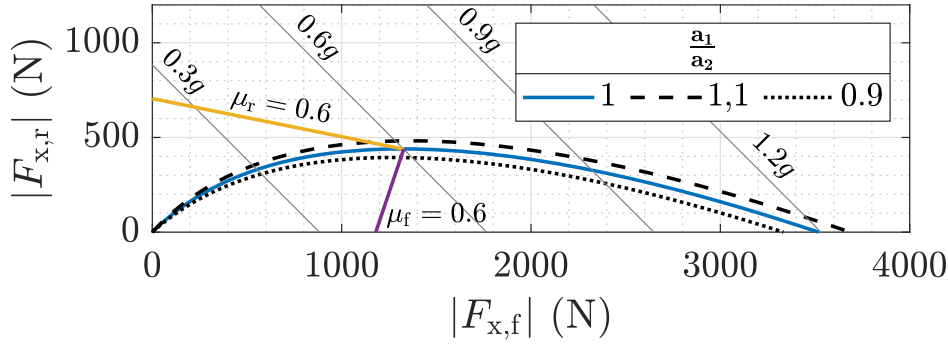


Figure 4.14: Ideal Braking parabola on float road for vehicles with the center of mass at mid-wheelbase ($a_1 = a_2$), forward ($a_1 > a_2$) and backward ($a_1 < a_2$).

The Braking bias (β_{brk}) is the braking force ratio between the front and rear axles and is defined as:

$$\beta = \frac{F_{x,f}}{F_{x,f} + F_{x,r}} \quad 4.113$$

When β is equal to zero means rear braking only, while β_{brk} is equal to 1 means front braking only. Other values of this latter bias mean a linear combination of rear and front braking. The ideal braking bias can be found when both tires reach their adherence limit at the same instant. This latter condition leads to the following system of equations:

$$\begin{cases} m\ddot{x}_G = -F_{x,f} - F_{x,r} - F_{x,\text{air}} - W \sin(\theta) - W c_{rr} \cos(\theta) \\ |F_{x,r}| = \mu_x F_{z,r} \\ |F_{x,f}| = \mu_x F_{z,f} \\ F_{z,f} + F_{z,r} + F_{z,\text{air}} = W \cos(\theta) \\ F_{z,r} a_2 + W \cos(\theta) c_{rr} h + M_{y,\text{air}} = F_{z,f} a_1 - h(F_{z,r} + F_{z,f}) \end{cases}$$

solving the system for $F_{z,r}, F_{z,f}, F_{x,r}, F_{x,f}$, and $\ddot{x}_G$; the rear and front ideal force, normalized by the weight result in Equations 4.114 and 4.115 respectively.

$$\frac{F_{x,r}^i}{W} = \frac{\mu_x}{W w_b} [h(-W \mu_x \cos \theta + F_{z,\text{air}} \mu_x - W c_{rr} \cos \theta) + a_1(W \cos(\theta) - F_{z,\text{air}}) - M_{y,\text{air}}] \quad 4.114$$

$$\frac{F_{x,f}^i}{W} = \frac{\mu_x}{W w_b} [h(W \mu_x \cos \theta - F_{z,\text{air}} \mu_x + W c_{rr} \cos \theta) + a_2(W \cos(\theta) - F_{z,\text{air}}) + M_{y,\text{air}}] \quad 4.115$$

Neglecting the aerodynamic effect, the rolling resistance, and the road slope Equation 4.114 is reduced as Equation 4.116, and Equation 4.115 as Equation 4.117.

$$\frac{F_{x,r}^i}{W} = \frac{\mu_x}{W w_b} (a_1 - h \mu_x) \quad 4.116$$

$$\frac{F_{x,f}^i}{W} = \frac{\mu_x}{W w_b} (a_2 + h \mu_x) \quad 4.117$$

The ideal braking bias is the ratio between the ideal front force and the sum of the ideal rear and front forces as follows:

$$\beta^i = \frac{F_{x,f}^i}{F_{x,f}^i + F_{x,r}^i} \quad 4.118$$

substituting $F_{x,r}^i$ from Equation 4.114, and $F_{x,f}^i$ from 4.115 result that

$$\beta_{\text{brk}}^i = \frac{a_2(W \cos(\theta) - F_{z,\text{air}}) + h(\mu_x W \cos(\theta) - F_{z,\text{air}}\mu_x + W c_{\text{rr}} \cos(\theta)) + M_{y,\text{air}}}{w_b(W \cos(\theta) - F_{z,\text{air}})} \quad 4.119$$

and neglecting the aerodynamic effects, rolling resistance, and the road slope, the ideal braking bias as a function of the longitudinal adherence coefficient results as follows:

$$\beta_{\text{brk}}^i = \frac{b + h\mu_x}{w_b} \quad 4.120$$

In the simplest case, the ideal braking bias has a linear relationship with the adherence coefficient. Observing that $F_{x,r}$ and $F_{x,f}$ can be expressed by F_D and β_{brk} , the system of equation can be manipulated as follows:

$$\begin{cases} F_D = F_{x,f} + F_{x,r} \\ \beta^i = F_{z,f} / (F_{z,f} + F_{z,r}) \\ m\ddot{x}_G = \beta^i F_D + (1 - \beta^i) F_D - F_{x,\text{air}} - W \sin(\theta) - W c_{\text{rr}} \cos(\theta) \\ F_{z,f} + F_{z,r} + F_{z,\text{air}} = W \cos(\theta) \\ F_{z,r} a_2 + W \cos(\theta) c_{\text{rr}} h + M_{y,\text{air}} + h F_D = F_{z,f} a_1 \end{cases}$$

The second equation of the system came from imposing the same adherence on both tires. Solving the system for $F_{z,r}, F_{z,f}, \beta^i$, and $\ddot{x}_G$ follows that the ideal bias can be expressed also as

$$\beta^i = \frac{a_2(W \cos \theta - F_{z,\text{air}}) + h(F_D + W \cos(\theta) c_{\text{rr}}) + M_{y,\text{air}}}{w_b(W \cos(\theta) - F_{z,\text{air}})} \quad 4.121$$

The braking bias also holds for traction by replacing F_D with $-F_D$, which means the driving force is positive according to the reference system.

All the formulae before can be summarised by the envelope performance shown in Figure 4.15. The blue line represents the friction limits, often referred to as the friction circle or Kamm's circle. The red lines represent the limit for a propulsive bias defined as follows:

$$\beta = \begin{cases} 1 & \text{if } \ddot{x}_G < 0 \\ 0 & \text{if } \ddot{x}_G \geq 0 \end{cases} \quad 4.122$$

which indicates only rear traction during acceleration and cruising, and only front braking during deceleration. The light gray highlighted area represents the admissible region for the motorcycle.

The wheelie and stoppie limits increase with the lateral acceleration, due to the motorcycle's roll. The higher the roll angle and the lower the center of gravity from the ground, and from Equation 4.90 is intuitive the increment of longitudinal acceleration for the wheelie limit. The wheelie limit for the motorcycle in this case is 0.93 g, while the stoppie limit is -1.07 g. This difference is given by the center of mass location. Furthermore, including the aerodynamic force, which counteracts the pitching moment during braking, the stoppie and wheelie limits are also functions of the speed, and the diagram is called GGv, where V stands for velocity.

The dark grey area is an extension to the admissible region implementing the ideal braking described in Equation 4.118. With the latter propulsive partition, the limit can be extended up to the friction limit imposed by the contact between the tire and the ground. Although the envelope increment is marginal for the ideal bias compared to the bias described

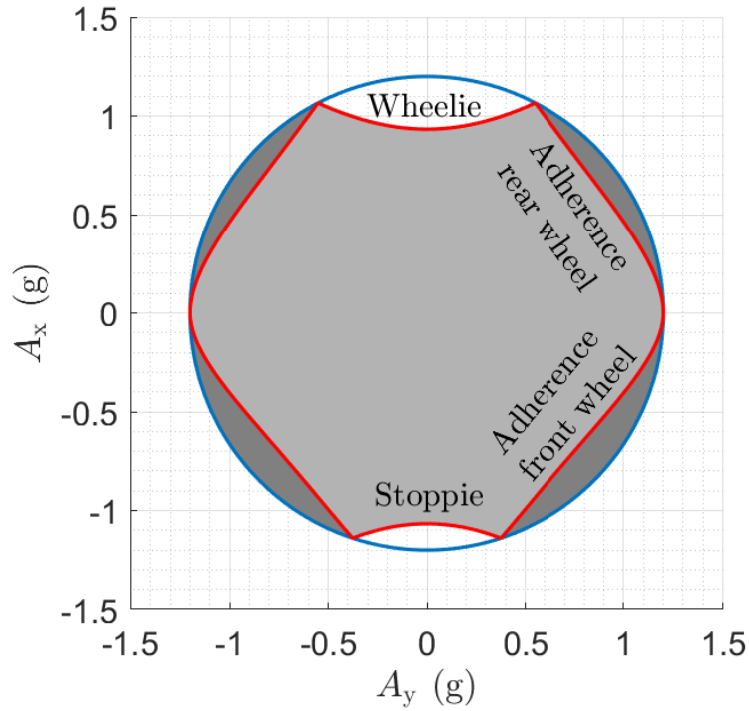


Figure 4.15: Shows the motorcycle envelope performance and the admissible regions. The light grey highlighted area is the region that is admissible for only rear traction and only front braking. The dark gray highlighted areas can be reached with the ideal bias.

in Equation 4.122, it could be the difference between the vehicle loose control or not during high-performance manoeuvres.

The ideal bias allows an increment of performance, which could be significant for high-demand adherence, like during a race competition. Furthermore, commuting or fun riding might also benefit from the ideal propulsive bias in situations of poor adherence. The circle or better ellipse adherence limit is shrunk for low value maximum adherence, and so extending the admissible region will provide a higher margin from the adherence limit, during common manoeuvres or typical riding in poor adherence conditions.

5. DRIVING CYCLES SYNTHESIS

5.1 Method and Data

Under section 2.1.2, the initial phase in creating a driving cycle involves selecting the route and the vehicle. For this study, a Ducati Streetfighter V2 was selected, which is a motorcycle powered by an internal combustion engine with a peak nominal power of 115 kW. Despite the absence of an electric model from the company, this motorcycle serves as an example of a good general benchmark for a sport motorcycle. The route was selected among the standard dynamic cycles by the testing department, which are usually used for suspension set-up and other tests. Due to privacy considerations, the specific route is not disclosed, but it is comparable to a country/mountain route.

The data were collected through an instrumented motorcycle that could record the motorcycle's onboard system and the GNSS signals. The data were processed and statistically analyzed, and illustrated in the section 5.2. After the analysis, the features were selected, and then the Markov states were defined as feature functions. These latter states form the set of all the possible system configurations. The state space was discretized, and the transitions between states were written in a matrix form, called the Transitional Probability Matrix (TPM).

For building the driving cycle, a method based on Markov Chain was introduced by the author in the subsection 5.3. This latter method was compared with the classic Markov Chain described in subsection 2.1.2. Then, a comparison between the new method and the conventional Markov Chain was used to set a benchmark for the constructive method developed and applied in this work. The method is based on an incremental approach, through random walks, several state predictions were constructed and added to complete a single driving cycle. This latter method builds speed schedules, trying to minimize the difference in the performance values between the synthetic and the data. Only the speed profiles that had an error lower than a threshold were validated and can be considered a driving cycle; the entire procedure is summarized in Figure 5.1.

While the speed was also provided by the wheel signal recordings, the vehicle speed used during the process was sourced from the GNSS data. The reason is that the wheel speed signal could vary considerably from the vehicle's speed, like when the wheel is locking. Furthermore, the GNSS acquisition could also be available more easily on other vehicles without

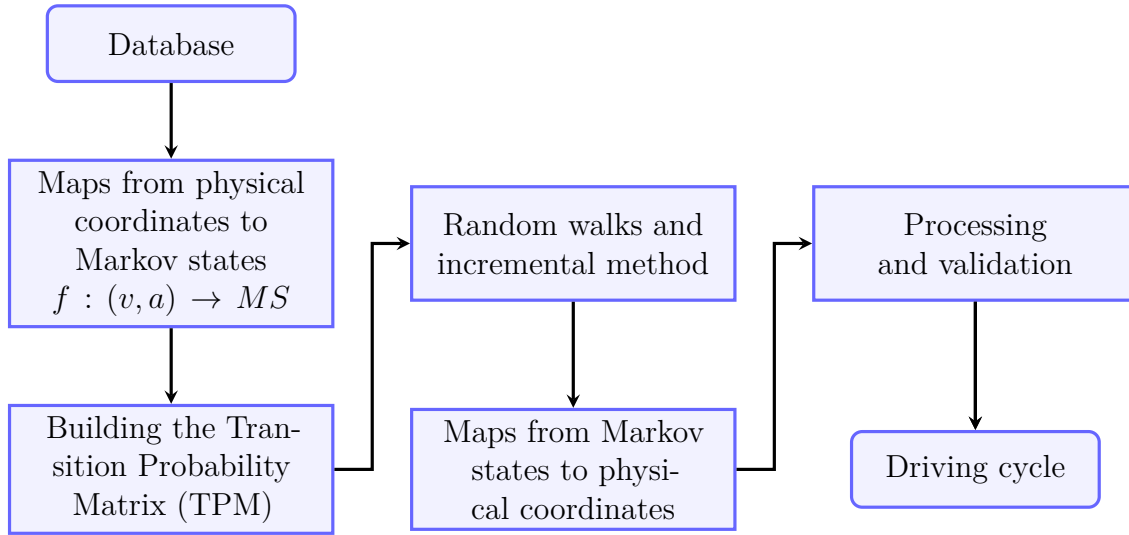


Figure 5.1: Flowchart of the procedure to synthesize a driving cycle from real-world driving data. The data are processed, and after the Markov states definition, the Transition Probability Matrix is constructed. Then the Monte Carlo method and the incremental method were applied for the synthesis of driving cycles. Finally, the speed profile was processed and validated. Only the validated speed profile is a proper driving cycle.

the need to fully instrument a motorcycle. However, the GNSS signal may be weak, resulting in gaps in data collection. The raw data were processed to reduce noise via a low-pass filter with a cut-off frequency of 2 Hz. The data with a bad GNSS signal were removed. Under these conditions (the same route and motorcycle), the data set was considered homogeneous and representative of a typical sport motorcycle tour. The speed profiles were divided into *key-on/off* events. These latter events were defined via the motorcycle turning on and side kickstand closure, while the events ended with the vehicle turning off or opening the side kickstand. An example of *key-on/off* event is shown in Figure 5.2. From all the data, the complete (i.e. no missing speed signal) events were collected, for a total of 101 micro-trips (MT) and almost 387 km traveled. The MTs are the driving activities between two stops.

5.2 Data analysis

The high-performance motorcycle allows high acceleration as well as high deceleration. The riding behavior could be different compared to high-performance car driving, due to the possibility of filtering, overtaking, and higher acceleration. On urban roads, the vehicle speed is bounded due to the presence of other cars, traffic lights, cross junctions, and other agents/infrastructures. The experimental data show a different riding style to the WMTC (Figure 5.3), with high acceleration (up to 8.5 m/s^2) and high deceleration (up to -10.9 m/s^2). The average speed was 61.8 (km/h), the average driving speed was 67.4 (km/h), and the speed standard deviation was 31.3 (km/h).

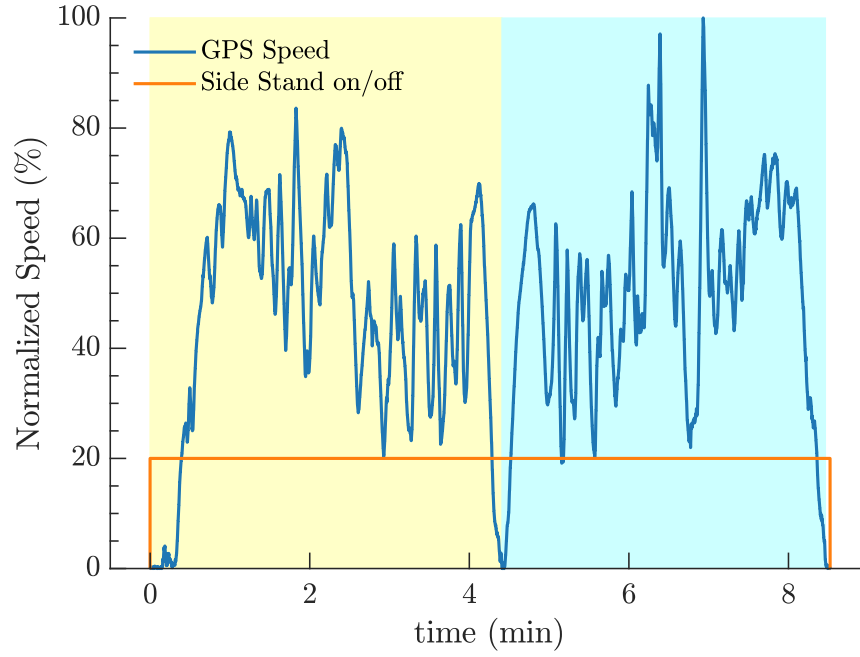


Figure 5.2: Normalized speed profile of a key on/off event. The event was determined by the side stand closure. This event was compounded by two micro-trips, whose duration is shown by the highlighted areas.

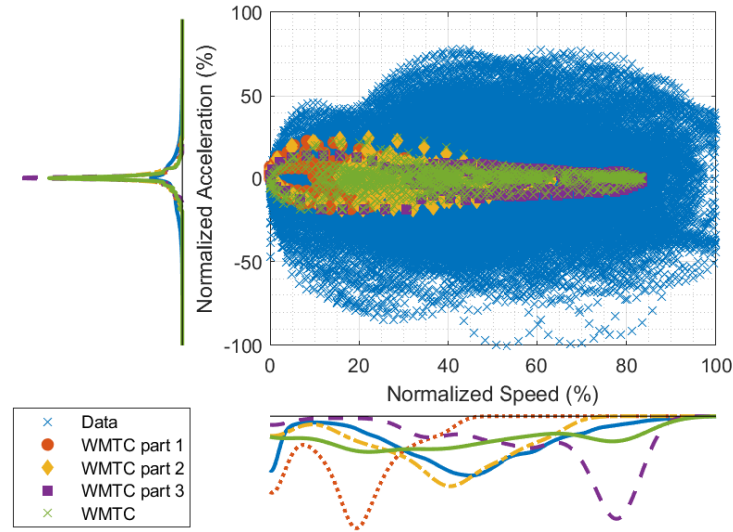


Figure 5.3: Speed and acceleration probability density (SAPD) comparison between experimental data and WMTC.

Furthermore, harsh acceleration and deceleration occurred for different speed values, while for WMTC at high speed, the acceleration is close to zero. Neglecting idle time is equal to focusing just on micro-trips. Even if the specific fuel consumption is higher when the vehicle is at rest, the absolute value of fuel consumption is low. Data were divided by micro-trips, and then 32 features were extracted. Pearson's correlation between these latter figures is reported in Figure 9.1 in the appendix. Table 5.1 reports several strong Pearson correlations between the characteristics. The km traveled is perfectly correlated to the fuel (0.99). A perfect correlation was also found between the time and the km

traveled because there is zero idle time in a micro-trip. The aerodynamic speed (V_{aer}^2) has a strong correlation with the average speed (0.96), the maximum speed (0.91), and the speed standard deviation (0.92). These speeds were all strongly correlated, so just using one among them is sufficient. Fuel performance ($\overline{Fuel}$), which is the liters of fuel divided by the distance, was collected during the riding and was strongly correlated (0.81) to the characteristic acceleration ($\tilde{a}$). This latter acceleration was correlated (0.69) with the average power (pwr_{avg}). The aerodynamic speed was correlated with the average positive power (pwr_{avg}^+), the average of the only positive power values. The torque features (trq) were fiercely correlated with their equivalent power features. The relative positive acceleration (RPA) was strongly correlated with the positive average acceleration (0.94) as an aspect of the RPA definition. Among these features, a subset can be chosen based on the correlation, such as between the km, time, and fuel; only the first one may be selected.

Table 5.1: Strong Pearson’s correlation (r) among features

Feature	Feature	r	Feature	Feature	r
km	time	0.99	RPA	a_{avg}^+	0.94
km	Fuel	0.98	V_{aer}^2	pwr_{max}	0.79
$\overline{Fuel}$	$\tilde{a}$	0.81	trq_{max}	pwr_{max}	0.95
V_{aer}^2	V_{avg}	0.96	trq_{avg}^+	pwr_{avg}^+	0.98
V_{aer}^2	V_{max}	0.91	trq_{avg}	pwr_{avg}	0.93
V_{aer}^2	σ_v	0.92	V_{aer}^2	trq_{max}	0.77
V_{aer}^2	pwr_{avg}^+	0.83	$\tilde{a}$	pwr_{avg}	0.69

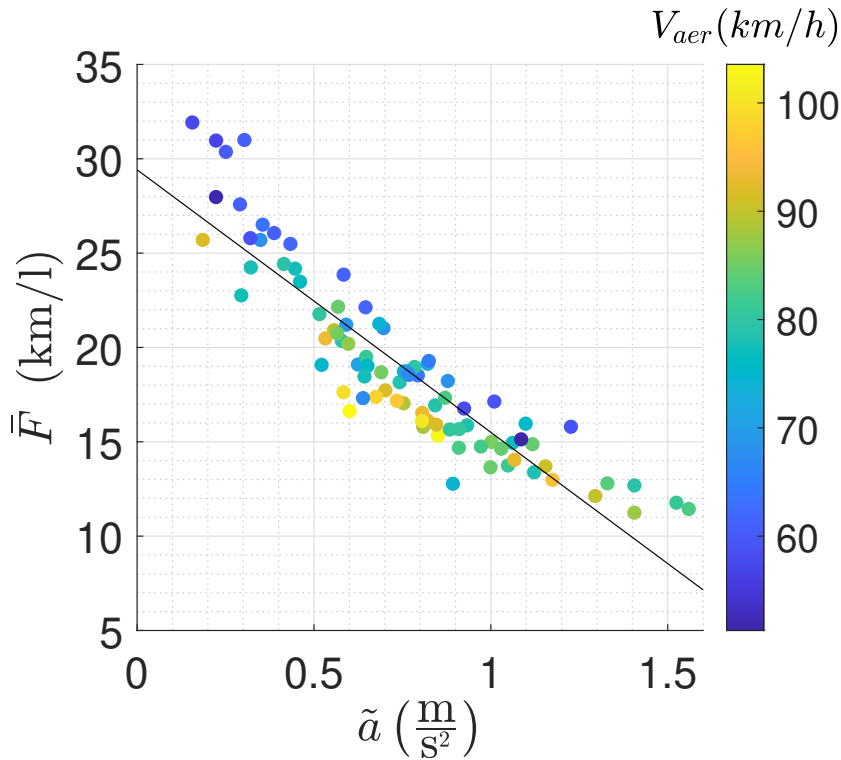


Figure 5.4: Micro-trips fuel consumption vs characteristic acceleration for all micro-trips longer than 1 km. A linear fit obtained an R^2 of 0.82 and a root mean square error of 2.05 km/l. The color indicates the aerodynamic speed magnitude; high values tend to lie below the line (worst consumption), and low values tend to lie above.

Figure 5.4 shows the Fuel Performance ($\bar{F}$) vs the characteristic acceleration for micro-trips longer than one kilometer. The latter figure reveals the high influence of the characteristic acceleration on consumption. A linear regression solely based on the characteristic equation yields an R^2 value of 0.82 and an RMSE of 2.05 km/l. Two models were developed based on the $\bar{F}$ values to forecast consumption utilizing solely cycle metrics. A two-layer neural network was trained on a data subset and validated on the remaining data, while for the regression analysis was used the cross-validation. Figures 5.5a and 5.5b show the specific fuel prediction using just the characteristic acceleration and the aerodynamic speed by two layers of neural networks, and a Gaussian process regression, respectively. This latter model was able to predict the consumption with an R^2 equal to 0.93 and an RMSE of 1.35 km/l, while the former model predicted the specific fuel consumption with an R^2 equal to 0.97 and an RMSE of 1.06 km/l. It was noteworthy that the specific fuel consumption ($\bar{F}$)

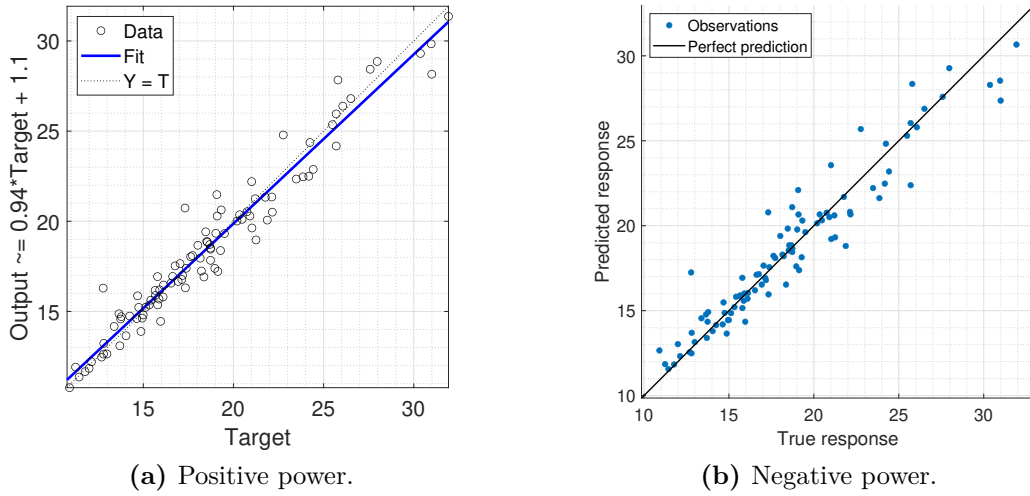


Figure 5.5: Shows the predicted fuel to km based on the characteristic acceleration ($\tilde{a}$) and aerodynamic speed (V_{aer}^2) employing both a neural network (on the left) and a regression method (on the right). The regression model achieves an R^2 value of 0.93 with a root mean square error (RMSE) of 1.35 km/l, whereas the neural network model attains an R^2 of 0.97 with an RMSE of 1.06 km/l.

prediction can be done with high accuracy without using any vehicle parameters. The two characteristic parameters were also able to capture the average engine power (clutch torque times engine speed) delivered in the micro-trips, indeed, a linear fit obtained an R^2 equal to 0.91 and an RMSE equal to 978 W. The average negative engine power was still well fitted by a linear relation on characteristic acceleration, and the aerodynamic speed with a R^2 equal to 0.77 and an RMSE of 884 W. Figures 5.6a and 5.6b show the average positive and average negative power vs the characteristic acceleration ($\tilde{a}$) and the aerodynamic speed (V_{aer}). The Pearson correlation between the average engine power and the aerodynamic speed was 0.82 (high correlation), and the correlation between the former power and the characteristic acceleration was 0.66 (moderate correlation). Because high accelerations are more common at low speeds (high gear ratio), which means high engine speeds and low vehicle speed, the power delivered at low vehicle speeds is generally lower than at high speeds. In this latter situation, the power delivered is dissipated primarily to counteract the aerodynamic drag, the possible acceleration is lower and becomes null at the maximum vehicle speed. The normalized root mean square error (NRMSE) for the two fits was 5.56% and 9.5% for the positive and negative power. The simplicity of the models is a good result for both power

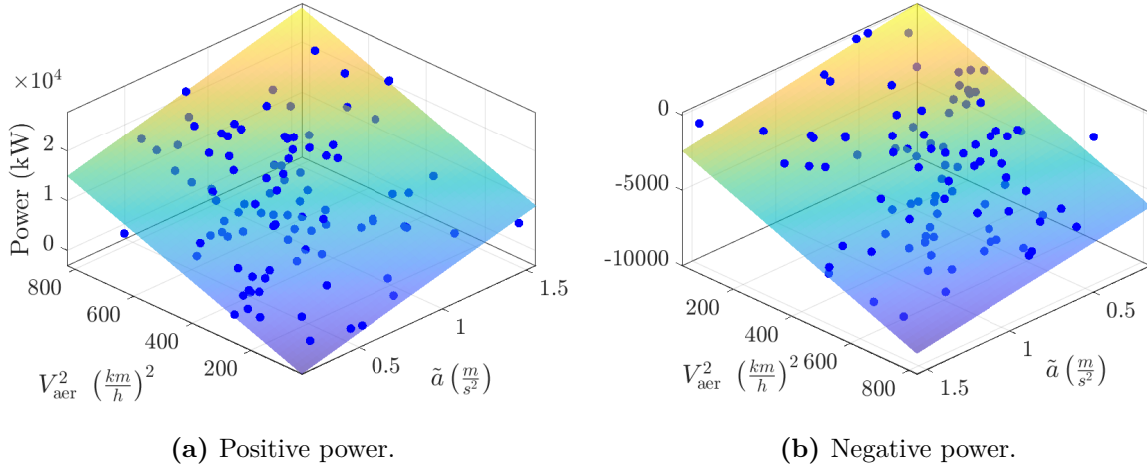


Figure 5.6: **a)** shows the average engine positive power vs the characteristic acceleration $\tilde{a}$ and the aerodynamic speed (V_{aer}). These two latter parameters were able to capture the positive power, a linear fit obtained an R^2 of 0.92 with an RMSE of 1543 W. **b)** shows the average negative engine power, with an R^2 equal to 0.78 and an RMSE of 884 W.

regions. Figure 5.7 shows the optimal number of clusters for the K-means algorithm. The distance between data was defined as cosine, correlation, and Euclidean on MATLAB. The former distance is one minus the cosine similarity (angle between points treated as vectors), so parallel points have a distance of null, and perpendicular points have a distance of one. The correlation distance is calculated as one minus the sample correlation between points. Finally, the Euclidean distance is the line length between two points. The correlation distance obtained the best results for the two clusters. The goodness of the clustering can be calculated via some scores, like the silhouette index. Namely, these latter scores are considered a good result when elements of the same cluster are close to themselves and are far from the other clusters.

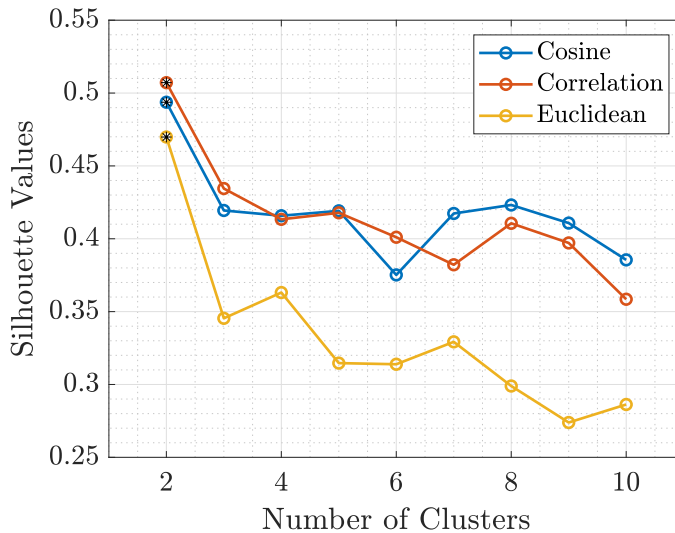


Figure 5.7: Evaluation of the optimal number of clusters for the K-means algorithm with three different distances, cosine, correlation, and Euclidean.

The silhouette score measures how much *similar* an element is compared to its cluster via comparison of its tightness and separation [250]; the silhouette score is shown in Figure

5.8. The silhouette score ranges from minus one to one for each single point. The higher the value, the higher its coherence is with its cluster and does not fit with the other clusters. Negative values mean that the element belongs more to other clusters than its own.

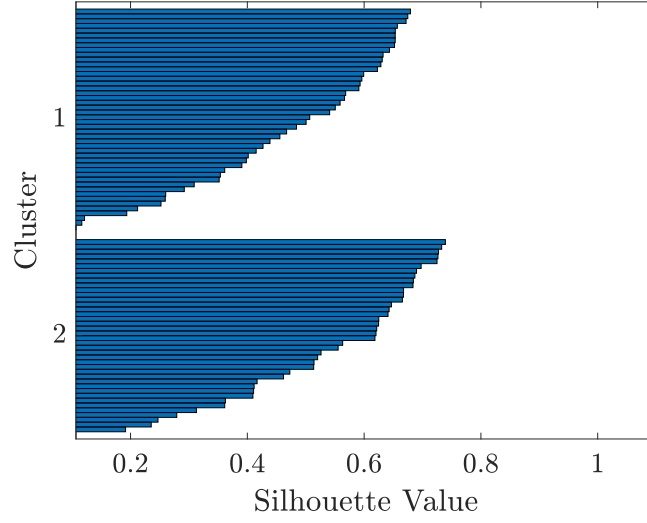


Figure 5.8: Silhouette index for the K-means clustering. The silhouette score has an average equal to 0,51.

The final score is calculated as the average width of each silhouette score among all the elements [250]. The Principal Component Analysis can be applied to reduce dimensionality without losing important information on the data. This latter analysis allows the definition of a new base via vectors (principal components) composed of linear combinations of the current vector space. The idea is to find a lower-dimensional space to represent the data. At the same time, the original data variation should be unchanged as much as possible. The new coordinates are a linear combination of the original variables. The clever idea behind this is to isolate the information by looking at the transformed data in a new space. The standard linear principal components analysis is based on the eigenvectors of the covariance matrix, and it gives the direction in which data have maximal variance. While the transformed variables (features) are the principal components (PCs), the individual transformed elements are the PC scores. Finally, by including the PCs with the higher eigenvalues in the analysis, it is possible to reduce the dimensionality by choosing a trade-off between the number of PCs and the amount of variation. The results by clustering with the PCA method are shown in Figure 5.9, for 16 variables of the 33 extracted, to reduce the redundancy due to the correlations.

Observing the centroids (blue cross) of cluster 1, it appears that this cluster generally exhibits a reduced acceleration percentage and power, resulting in an increased km per liter ($\overline{Fuel}$). On the other hand, looking at the other centroids (orange cross), this second cluster tends to have higher average power, higher aerodynamic speed, and higher speed consumption. Figure 5.10 shows the distribution feature by feature by groups, for the km traveled, the km to liter or fuel performance, the aerodynamic speed squared (V_{aer}^2), the characteristic acceleration ($\tilde{a}$), and the average power. There is some overlap between the two clusters, as for the km-to-characteristic acceleration, as expected by the silhouette score of 0.51, which indicates a good clustering. Box charts in figure 5.11 show the median, the second and third quartile for four features, helping to further understand the cluster meaning.

Cluster two has higher km traveled, lower fuel performance, higher aerodynamic speed, and higher characteristic acceleration. Cluster one counts 40 micro-trips, while cluster two

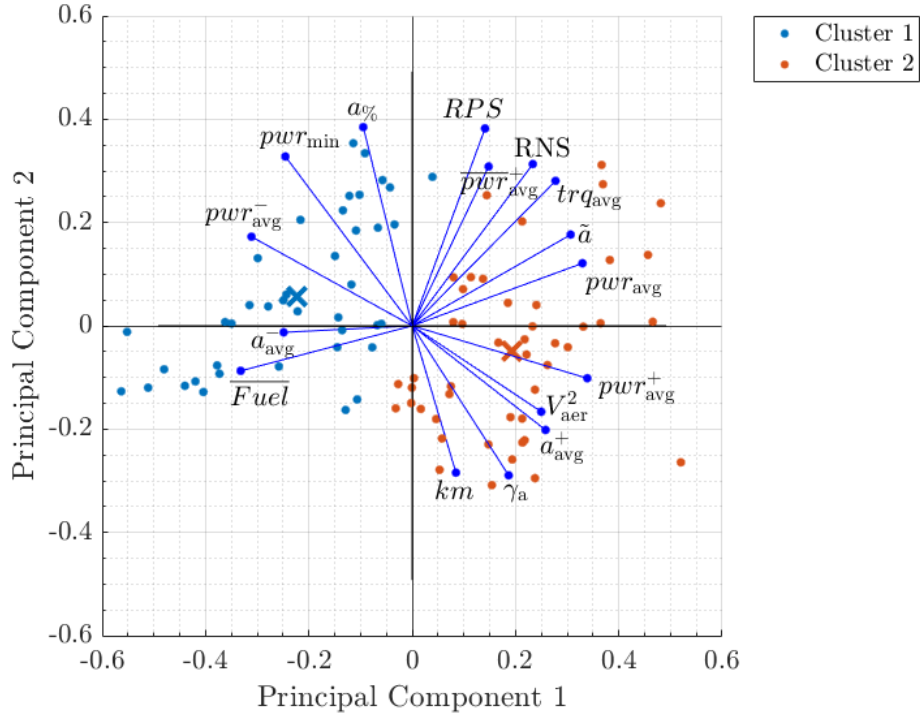


Figure 5.9: Data plot on the first two principal components plane. The x crosses are the cluster centroids. The original variables are reported as vectors; the principal components are linear combinations of these latter variables.

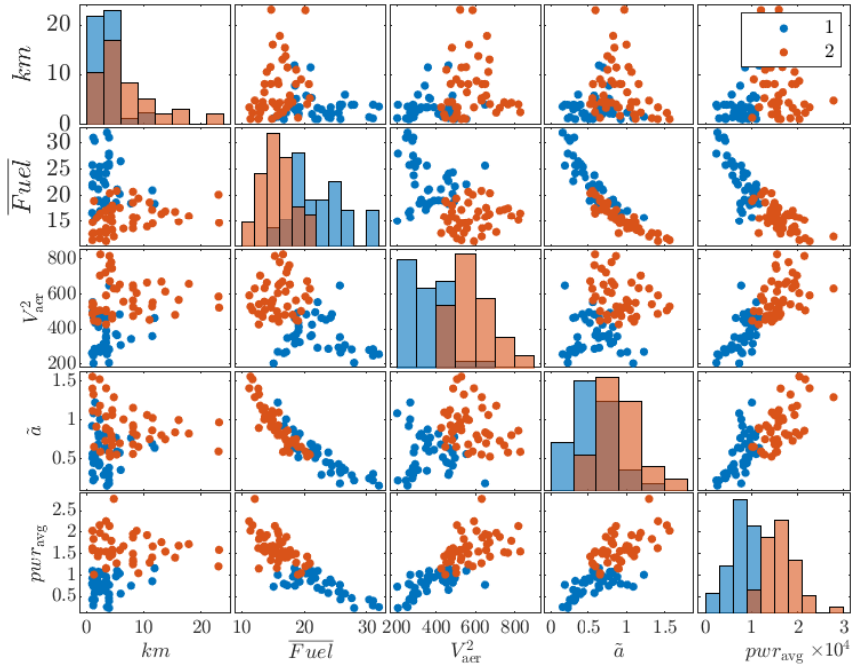


Figure 5.10: Distribution of five features divided by two clusters. The features are the km traveled, the km to fuel liter, the aerodynamic speed, the characteristic acceleration, and the average power.

counts 46. The median km value is 3,17 and 3,44 for clusters one and two, respectively. The median fuel performance value is 21,95 km/l for cluster one and 15.83 km/l for cluster two. The aerodynamic speed is highly correlated to the average speed as results from the correlation analysis (0.96 Pearson coefficient), and the median values were 350,9 and 559,8 (km/h)² for clusters one and two. Finally, the $\tilde{a}$ is the specific work due to kinetic and potential energy increment, and was highly correlated to the fuel performance. The second cluster has a higher median $\tilde{a}$ value (0.88) than the first cluster (0.57). The WMTC has a relative positive acceleration value (RPA) of 0.151 (ms⁻²). This latter acceleration is an index of driving *dynamicity*, and the data have an RPA value of 0.71, which is more than four times the WMTC data.

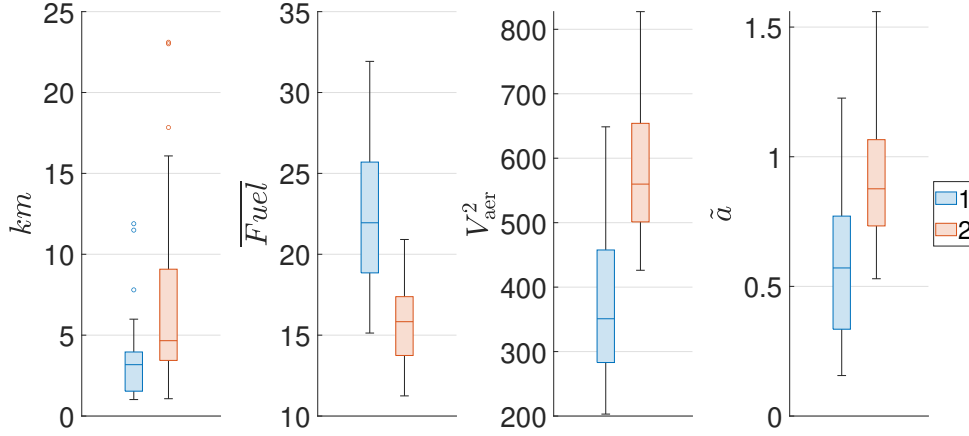


Figure 5.11: Box chart of four features, the km traveled, km to fuel liter, the aerodynamic speed, and the characteristic acceleration. Data are grouped into the two clusters found.

In conclusion, the data were processed and analyzed, deriving a set of statistics and features to describe them. From correlation analysis, a subset of features was selected for clustering the data. Two distinct clusters were identified, and 40 micro-trips for cluster one, and 46 for cluster two. Out of the 101 micro-trips, those with a distance of less than one kilometer were excluded. Cluster 1, represented on average by the blue cross centroid in figure 5.9, is characterized by lower acceleration percentage, lower average power, leading to increased fuel efficiency (km per liter). Cluster 2, represented by the orange cross centroid, exhibits higher average power, aerodynamic speed, and consequently, higher fuel consumption. These clusters underscore the significant impact of driving patterns on fuel consumption efficiency. The data analysis highlights the effectiveness of using characteristic cycle metrics ($\tilde{a}$, V_{aer}^2) without additional vehicle parameters to predict specific fuel consumption accurately.

5.3 Constructive method

The method developed and proposed here is based on a Markov-Chain Monte Carlo (MCMC) approach *forced* to reduce the Performance Value (PV) or residuals to zero. The MCMC method was already successfully applied for the synthesis of driving cycles after defining the Markov states by longitudinal speed and acceleration [80, 163, 266]. The MCMC method implemented in this work was based on a discrete-time and time-homogeneous Markov chain model (DTHMC), which is a sequence of random variables (stochastic process), with the Markovian property, also known as the memoryless property. This latter

property can be summarised as the state at any given time (i_n) gives all information about the past, and it is the only one relevant to the future state (i_{n+1}). That is, the past outcomes of the stochastic process do not influence the next outcome. A mathematical description is given in the following equation:

$$P(X_{n+1} = i_{n+1} \mid X_n = i_n, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) = P(X_{n+1} = i_{n+1} \mid X_n = i) \quad 5.1$$

where $\{X_n, n = 0, 1, \dots\}$ indicates the random variable at the time $t = n$. The notation p_{ij} indicates the transition probability of transferring from state i to state j in one time step, for the mathematical meaning see equation 5.2. The transition probabilities between all the states can be rewritten in a matrix form, called the Transition Probability Matrix (TPM). The evolution of the Markov chain is determined by the transition probability matrix given the initial state π_0 .

$$p_{ij} = P(X_{n+1} = j \mid X_n = i) \quad 5.2$$

The probability distribution after one step is given by the product of the transition probability matrix and the initial state as follows:

$$\pi_1 = TPM \cdot \pi_0 \quad 5.3$$

The processes can be repeated to obtain the next step distribution, multiply the current state by the transition probability matrix as follows:

$$\pi_2 = TPM \cdot \pi_1 = TPM \cdot TPM \cdot \pi_0 = TPM^2 \cdot \pi_0 \quad 5.4$$

leading to the general formulae to find the n-th probability distribution:

$$\pi_n = TPM^n \cdot \pi_0 \quad 5.5$$

After constructing the TPM, speed time series (DCs) could be obtained by simulation of the Markov Chain state walk, or, namely, a random walk through a sequence of the MC states. The random walks were simulated in MATLAB based on a uniform probability density and the Monte Carlo approach. The states or classes must be defined via physical signals to construct the TPM. In this work, the classes were defined by the longitudinal velocity ($\hat{v}$) and acceleration ($\hat{a}$), and road slope ($\hat{\theta}$) after their discretization via constant delta values for each vector ($\hat{v}$, $\hat{a}$, $\hat{\theta}$). Figure 5.12 shows an example of the speed-acceleration space discretization.

A Markov fine mesh was implemented in this work (192 591 states). Acceleration, speed, and road grade delta step were 0.18 m/s , 0.1 m/s^2 , and 0.1° respectively. The mesh was sized as a trade-off between a good vector space discretization (needed due to the high sport motorcycle acceleration) and the computational time and memory needed for synthesis. Indeed, the TPM has elements as many as the states squared. As shown in Figure 5.12, some states were physically meaningless and thus avoided their definition, like the states above the maximum power. Instead of defining all the possible states, only the states that occurred at least once were implemented to construct the TPM. A non-homogeneous distributed mesh that collects the difference in consumption might be used to reduce the number of states or the error introduced by the discretization. The process proposed in this work was based on an *incremental* method. The initial state ($v(0) = 0$, $a(0) = 0$, $\theta(0) = 0$) was chosen, and one random walk was performed. The last state obtained was set as a new beginning state, and a finite number (n_i) of random walks of the same length (l_i) were synthesized (figure 5.13a) where the subscripts i mean the i-th time step. The random walk quantity and duration might be different for each iteration, but fixed values for both parameters

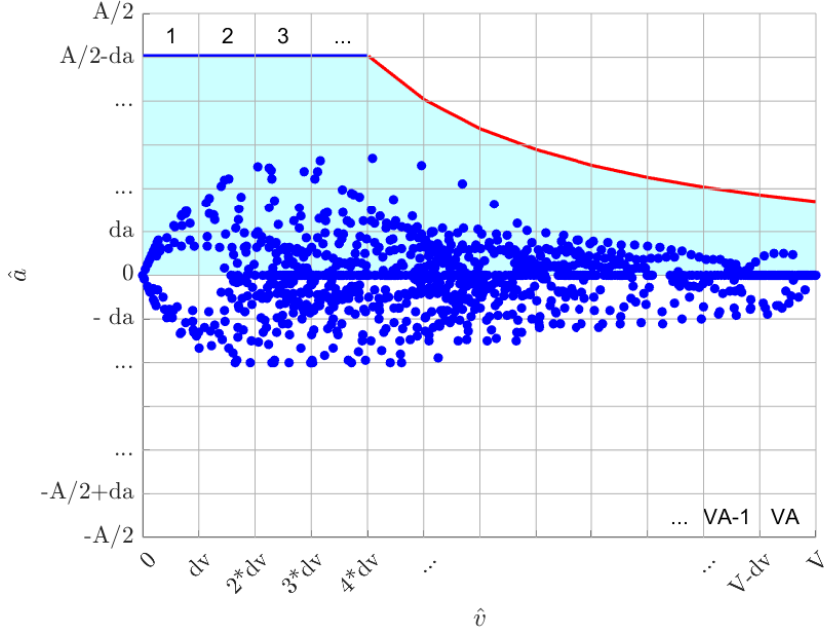


Figure 5.12: Example of the speed-acceleration space discretization. The first three classes are indicated in the top left corner by numbers 1, 2, and 3. The highlighted area (cyan) represents the achievable classes for a ground two-wheel vehicle; the top blue line indicates the wheelie limit, and the red line indicates the maximum power limit. WMTc operating points are also shown (blue dots).

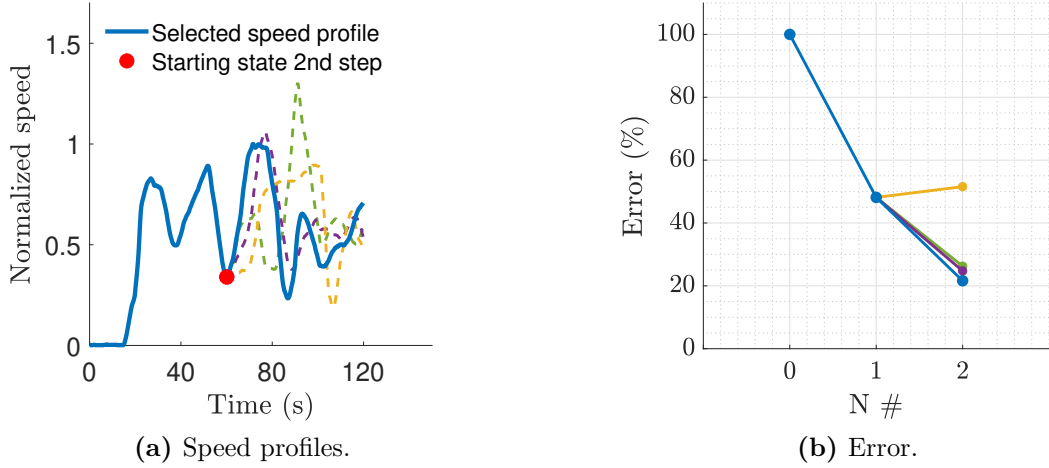


Figure 5.13: Evolution and selection of the speed profiles (a). The blue line had the lowest error among the others (b).

were chosen. Between all the outcomes simulated, the random walk, added to the previous part, that reduced the most the performance value was the one selected (Figure 5.13b). The procedure at the next time step was repeated, setting the initial state equal to the last one generated and selected.

The iterative speed profile building was repeated until the error was lower than or equal to a threshold or the iteration was higher than the maximum set. An example of residual minimization is shown in Figure 5.14. The final random walk was obtained as a union of shorter random walks selected to minimize the residual time step by time step. In other

building methods, the duration was chosen in advance for arbitrary reasons, while in this way, the length is a function of the error.

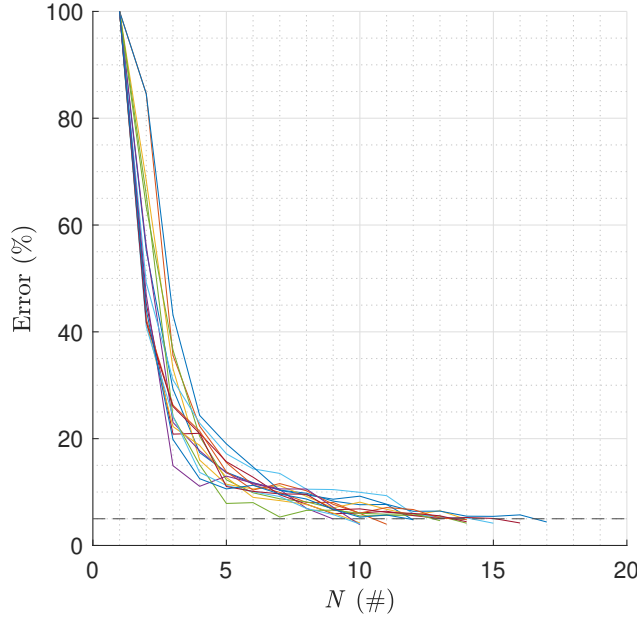


Figure 5.14: Fifteen runs of the iterative construction cycle. A run stops when the error equals or lowers a 5% threshold value.

The time step is crucial to define the transition probability matrix elements. The acceleration/speed mesh establishes the number of states and the TPM matrix elements, but the building of new driving cycles needs the discretization of time, too. The time was discretized with a fixed time step. Figure 5.15 represents the influence of delta time on information between one time step to the other. Given the speed at a certain time, increasing the time step reduces the information between one step to the other. The vehicle dynamics (like the maximum jerk) determined the minimum delta time needed to not lose information. For example, a train that travels at a constant speed and with low deceleration values might be described with a bigger time step than one used for road vehicles. Smaller dt values conserved more precise *information* about the speed series during the time. On the other hand, more calculations are needed for synthesizing driving cycles. A trade-off between the time step and accuracy could be evaluated. A linear fit over normalized present speed as a function of previous speed, for three different delta times (0.1s, 1s, 5s) obtained, and R^2 of 0.999, 0.966, and 0.656, with an NRMSE of 0.3%, 3%, 9.7%, respectively. Although the delta time of 1 second is good and is the common choice for the driving cycle building, in this work, the minimum allowed time step was chosen to have precise results. The time was discretized with a fixed time step, which was chosen equal to the time step of the data sampling (0.1 s), and the transition probability matrix was considered time-independent, by the definition of a homogeneous Markov Chain, it was not a function of time. *Sufficiently* long random walks have the same data distribution. An irreducible aperiodic chain will reach its steady-state distribution (π) in an amount of time (or steps) called the mixing time. For evaluating the density mesh goodness, long runs were used (30 times the data length). The synthesized speed profiles were then filtered to smooth the discontinuity derivation due to the discretization process. The incremental method was not applied to synthesize these long runs, because here was investigated and benchmarked the mesh density (i.e. state number) as a reference. A comparison of 9 features between the data and simulated speed profiles was

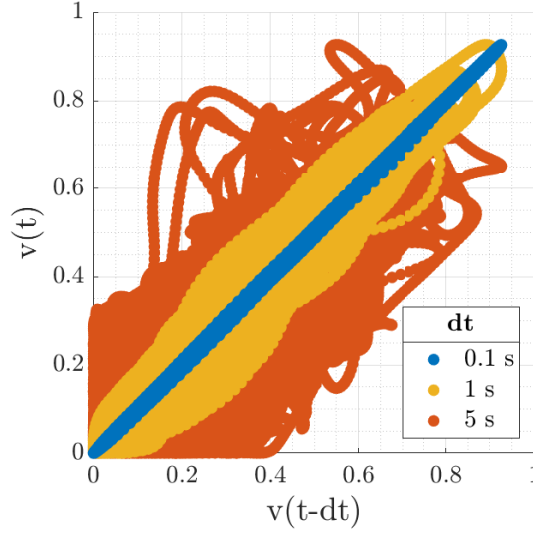


Figure 5.15: Normalized present speed $v(t)$ vs previous speed $v(t-dt)$ for three different delta time (0.1s, 1s, 5s). For dt tends to 0 we obtain $v(t)$ vs $v(t)$, equal to the bisector. Bigger values of dt mean bigger dispersion from the bisector.

reported in Table 5.2. Where v_{avg} is the average speed, v_{avg}^+ is the average positive speed (i.e. $v > 0$), σ_v is the velocity standard deviation, σ_a is the acceleration standard deviation, max speed is the maximum speed value, a_{max}^+ is the highest positive acceleration value, and a_{min}^- is the lowest negative acceleration value. The feature with the highest absolute relative error was the minimum negative acceleration (0.86%), while the lowest was max speed (-0.03%). For all the features, the error was lower than 1%.

Table 5.2: Relative error between data and synthetic speed profile long random walk.

v_{avg}	v_{avg}^+	σ_v	σ_a	v_{max}	a_{max}^+	a_{min}^-	RPA	$\tilde{a}$
-0.31 %	-0.15 %	0.06 %	0.44 %	-0.03 %	-0.13 %	0.86 %	-0.15 %	0.73 %

To compare the method introduced in this work and the classic Markov Chain Monte Carlo (MCMC) approach, in this section, the error or performance value was computed only on the speed distribution, and described in equation 5.6. Imposing an equal speed distribution means that the moments, such as the mean and variance, were the same as the data.

$$E = \sum \left(\sum_{i=1}^n |(v_{\text{sim}}(i) - v_{\text{data}}(i)) \cdot w(i)| \right) \quad 5.6$$

Weights (w) were introduced to reduce or exclude the influence of same-speed bins such as high-speed values. The length of the single simulation (l_i) and the number of simulations (n_i) were kept constant until the random walk was done; thus from now on, the time subscript is omitted. When n was equal to one, there was no difference between this method and a classic random walk, independently of the l value. The speed profile length was kept constant (120 min) as were the speed profiles for different combinations of n and l values. These two variables (n, l) ranged from 1 to 5 with unitary step increments. The mean relative error and the mean computing time are shown in Figure 5.16.

The number of simulations for each step must be a natural number as well as for the simulation length. The lowest error was 1.53% for $n=5$, and $l=1$ or point (5,1). The highest

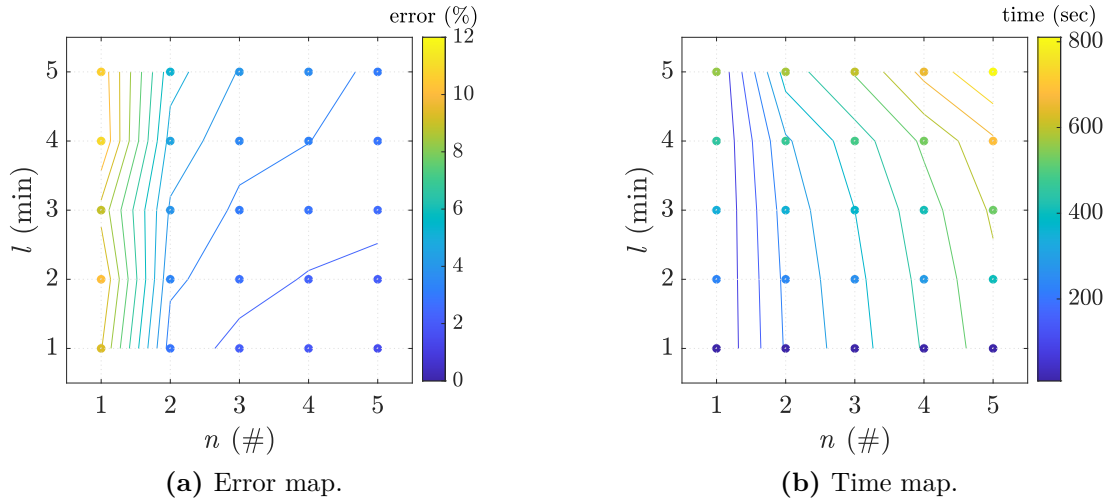


Figure 5.16: Relative error (a) and time (b) maps of the iterative method. The speed profile length was constant (120 min), and both the number of simulations for step (n) and the length of a single simulation (l) were changed. The dots are the numerical values, while the lines are the iso-error/time values calculated by data interpolation.

computing time was 810 seconds for point (5,5), and the lowest value was 8.9 seconds for point (3,1). The relative error was reduced by an n increment and became higher with an l increment as shown by the iso-error line in figure 5.16a. Increasing the parameter l for a low value of n did not influence the error as at high n values. An increment of n or l meant an increment in the computing time as shown in figure 5.16b. At low values of n , an increment of the other parameter took less time to compute than at higher values.

5.4 Case Study: Sport Motorcycle Driving Cycle

The method described in section 5.3 was applied to real-world motorcycle data. The speed profiles were recorded via GNSS and derivative by time to obtain the longitudinal vehicle acceleration. Data with missing speed values were excluded. These data were processed, and the DC features were extracted. Statistics metrics are summarised in the table 5.3. 300 DCs were synthesized via random walks and the *incremental* method with a 5% relative error. The error was computed as the weighted difference in speed and acceleration distribution. Specific consumptions were obtained via the vehicle model for each speed profile. Only the DCs with an error on $\tilde{a}$ and consumption lower than 1% were considered valid. Applying these criteria, only 11 of 300 cycles were validated (3.7%). Differences between the data and the mean value of all cycles and the validated cycles are reported in Table 5.3, with the WMTC values as reference.

The mean relative RPA error between data and validated DCs was -0.98%. The relative $\tilde{a}$ error between the data and the average validated DCs was practically null. The specific consumption was 80.69 and 81.33 Wh/km for the data and the validated DCs, respectively. The WMTC results differ significantly from the data, highlighting that a proper cycle is necessary for the right powertrain design, as well as energy consumption and pollution. The average distance was 49.59 km and 56.32 km for the synthetic and validated speed profiles, respectively. The time ranged from 31 to 76 minutes.

Including the road slope, the vehicle consumption increased from 77.8 to 81.33 kWh, due to the non-net altitude. The overall mechanical energy should be unchanged by the potential energy if the net sum is zero. Even so, the net altitude would be null, and the road slope

Table 5.3: Comparison between data, standard cycles, and synthesized driving cycle average results.

Cycles	v_{avg} (km/h)	v_{avg}^+ (km/h)	σ_v (km/h)	RPA (m/s ²)	$\tilde{a}$ (m/s ²)	$\bar{E}_T$ (Wh/km)	Distance (km)
Data	61.8	67.4	31.3	0.71	0.749	81.3	387
Synthetic DCs	61.31	66.94	31.11	0.696	0.745	81.64	49.59
Validated DCs	61.86	67.33	30.79	0.703	0.749	81.33	56.32
WMTC part 1	24.39	29.93	16.68	0.196	-	26.23	4.07
WMTC part 2	54.67	59.21	25.06	0.188	-	37.71	9.11
WMTC part 3	94.42	97.17	30.54	0.117	-	59.74	15.73
WMTC	57.83	64.01	37.88	0.154	-	48.09	28.91

modifies the powertrain operational point, changing the efficiency. For the same velocity, going uphill results in more required power than going downhill. Thus, for evaluating the real impact on the powertrain, the road slope must be included even if the net altitude sum is zero. A synthetic driving cycle with the altitude is shown in figure 5.17, called the Sport Motorcycle Driving Cycle (SMDC).

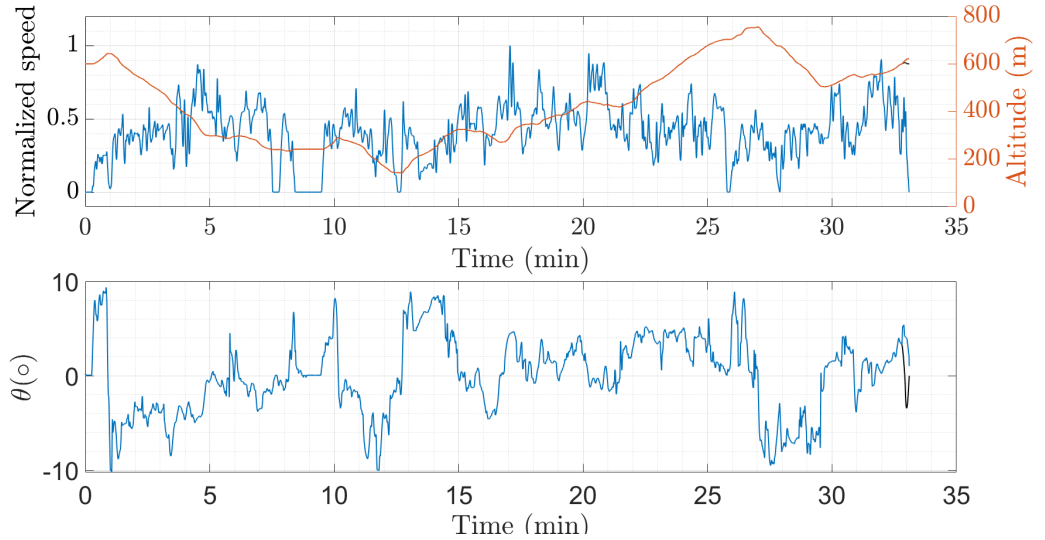


Figure 5.17: Shows the Sport Motorcycle Driving Cycle (SMDC) speed values and altitude on the top plot, and the road grade on the bottom plot. On black, the slight modification to obtain a zero net altitude.

The Sport Motorcycle Driving Cycles has an average velocity equal to 64.90 km/h, an average driving speed of 68.82 km/h, a speed standard deviation of 29.87 km/h, and a positive altitude of 21.43 m. The vehicle consumption was 81.27 Wh/km, where the average consumption including the altitude was 81.33 Wh/km, an error of -0.07 %. These latter results are reported in the table 5.4.

Although good results were obtained by the driving cycle, the net altitude is positive, and repeating this cycle several times to estimate the driving range or the emission will result in a gain of altitude. Thus, the last 20 seconds of the slope were modified to achieve a null altitude. The road slope was changed using a spline, resulting in a net altitude equal to $-5.06 \cdot 10^{-4}$, which is negligible for an implementation on a test bench. Modifying the road slope results in a lower characteristic acceleration of 0.746 m/s², and lower consumption of 81.05 Wh/km, with a relative error of -0.4% and -0.34%. The vehicle power distribution for

Table 5.4: Sport Motorcycle Driving Cycles comparison with data.

Cycle	v_{avg} ($\frac{km}{h}$)	v_{avg}^+ ($\frac{km}{h}$)	σ_v ($\frac{km}{h}$)	$\bar{E}$ $\frac{Wh}{km}$	$\tilde{a}$ $\frac{m}{s^2}$	distance km
SMDC	64.90	68.82	29.87	81.27	0.747	36
Data	61.80	67.40	31.0	81.33	0.749	387

the Sport Motorcycle Driving Cycle is shown in Figure 5.18. The maximum power is 66.57 kW, the minimum is -61.73 kW, the average power is 1.97 kW, the median power is 1.18 kW, and the standard deviation is 11.2 kW. The difference in power between the SDMC and the

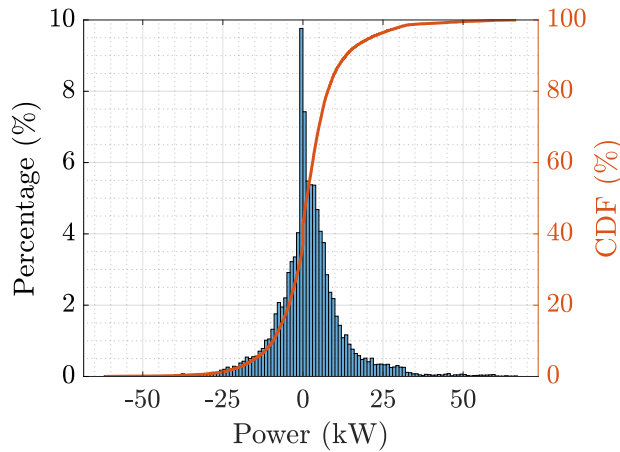


Figure 5.18: Shows the vehicle power distribution percentage on the left y-axis, and the cumulative density function on the right axis.

cycle without correction on the altitude is shown in Figure 5.19. This latter difference is only in the last 20 seconds. The road slope was reduced to obtain a net zero altitude to balance the 21.43 meters of altitude gain at every cycle. Reducing the road slope meant reducing the power, and a maximum difference of -775.2 w

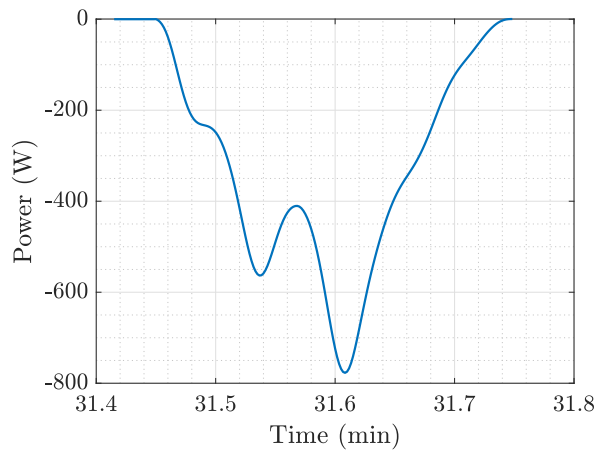


Figure 5.19: Power difference between the SMDC and the cycle without altitude correction. The difference is only in the last 20 seconds of the driving cycle.

In conclusion, the analysis of a sport motorcycle ride data shows that standard driving cycles misrepresent this kind of motorcycle. Thus, a driving cycle (SMDC) for representing

a sport motorcycle was built from real-world data, including the altitude. This latter cycle was missing among the other driving cycles developed, and often the altitude or road slope is neglected. To synthesize the Sport Motorcycle Driving Cycle, the incremental method was developed, which is based on the Monte Carlo Markov Chain method, modified to minimize the error between the reference data and the synthesized driving cycle. The main limitation is that the data was collected by an internal combustion engine motorcycle. although this fact, the kinematics vehicle is independent of the vehicle powertrain, and the SDMC is still a benchmark for an electric sport motorcycle.

6. POWERTRAIN LOSSES

6.1 Test bench and setup

Finding an architecture solution that satisfies both performance and range for electric motorcycles is challenging due to the electric powertrain's flexibility and constraints (like the low battery energy density). This chapter analyses the gearbox and powertrain efficiency for battery electric motorcycles (BEM) based on drive-train architecture and among vehicle use scenarios. The impact on consumption of a constant-speed gearbox was investigated, focusing mainly on load-independent losses. The analysis was performed via an analytical approach and experimental data. Two different gearbox and powertrain solutions were characterised by test bench experiments that ran them in free-driving conditions or no-load tests. A comparison of these powertrain solutions on consumption for the same motorcycle model and different speed profiles (WMTC, LA-4) was conducted. The results show the energy loss and provide information for defining drive-train components and architectures. In this chapter, the losses the gearbox gives are analysed for the no-load or free-driving condition. The powertrain consisted of an electric machine coupled to the gearbox with an integrated frame, so the full disengagement of this latter machine was impossible. The electric machine loss impacts vehicle consumption, and the procedure to estimate the riding range for the electric motorcycle was modified to account for them [254].

The selected motor was a radial flux Surface Permanent Magnet Synchronous Machine (SPMSM). This type of motor was chosen due to the strict demand for high performance. Motor selection was up to the company and was not dedicated to this type of research. For this reason, unfortunately, the precise specification cannot be disclosed. However, here is a brief overview: the motor had an 800V architecture, more than 6 poles, a maximum speed higher than 15000 rpm, and peak performance higher than 100kW and 100Nm.

The SPMSM is well suited for this application, because at high speed the power density (kW/kg) tends to increase. Thus, the motor can provide the power with a lower mass and a smaller volume, compatible with the volume of the vehicle. However, the maximum motor speed is a function of the radius, thus, high-speed machines usually have smaller volumes and lower torque but higher power density. Vehicle traction requires high torque at low speed and low torque at high speed, aligning well with these motor characteristics. Furthermore, the loss density increases, so reducing losses with effective methods and cooling of the machine

should be applied.

To allow the vehicle to coast down, the electric machine must work as a motor to equal the inherent losses. These latter losses for a SPMSM consist of copper loss (Joule effect), iron or core loss (hysteresis and eddy current), permanent magnet loss, friction, and windage loss [249]. Other sources of loss in this powertrain were converter loss due to the inverter, gearbox loss, and stray loss (non-uniform harmonics distribution). No-load losses were measured at constant speed, and their influence on consumption on driving cycles (UDDS, WMTC) was investigated. The battery loss was not investigated via the experimental test.

The powertrain characterised via the experimental test consisted of the inverter, the electric machine, and the gearbox. The system layout is shown in Figure 6.1. The liquid cooling system extracted the heat, and the bench has a dedicated external cooling tower to regulate the cooling temperature and dissipate the heat. Albeit in the no-load test, the motor losses and so the heat generated were minimal. The gearbox consisted of a single speed with

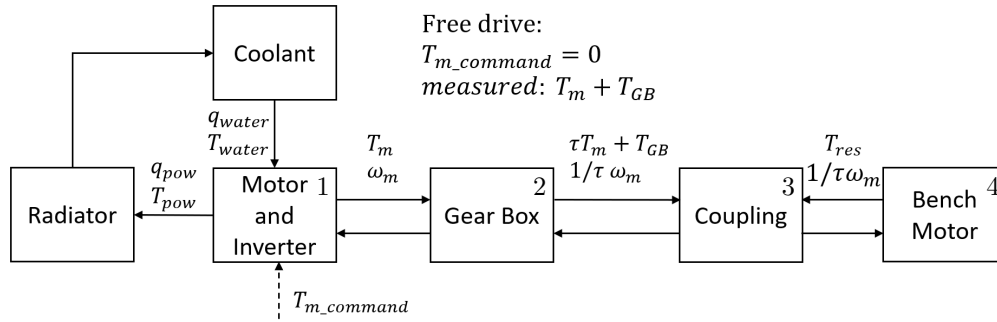


Figure 6.1: Shows the links between the powertrain components and the test bench. The motor and inverter (1) are mated to the gearbox (2), which is connected to the Bench motor (4) by a coupling joint (3).

three reduction stages. The gearbox was mated directly and rigidly with the motor shaft, then joined to the bench motor via a coupling. This latter motor acted as the resistance vehicle load during the moan monitoring phase of the powertrain and is shown in Figure 6.2. The torque applied at the coupling was recorded via load cells. Torque measurement is achieved via a static reaction type strain gauge using two linear gauges (TS CTS82500KC25) securing the rotation of the driveline. The motor speed used is read by the inverter with the motor resolver. It is a single syn absolute resolver (Tamagawa TSY1020) with an accuracy of 60' p-p and sampled above 10kHz. The power loss was calculated as the product of the torque and the speed. A battery simulator device was used to power the electric drive. The influence on consumption of the free-driving losses was evaluated using the vehicle model described in the chapter 4 and different speed profiles, which describe the vehicle kinematics.

Consumption was calculated as the battery energy spent by the vehicle due to the resistance force, normalized by the distance traveled. Two speed profiles were used as input: the Urban Dynamometer Driving Schedule (UDDS), also called LA-4, and the World Motorcycle Test Cycle (WMTC). These speed profiles are well-known and used for both conventional and electric vehicle consumption estimation via different norms.

6.2 No-load losses

The No-load test consisted of a zero resistance torque by the electric machine ($T_m = 0$), so the input power provided by the bench was ideally equal to just the gearbox loss. The motor losses consist of the stator copper loss, the core loss (i.e. hysteresis, and eddy currents

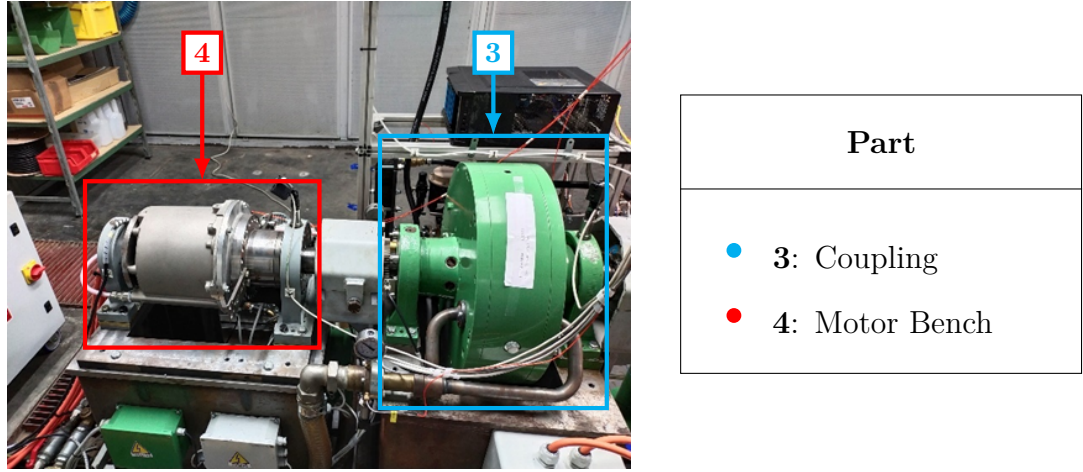


Figure 6.2: Shows the equipment used for the powertrain bench test. Parts 3 and 4 of Figure 6.1 are highlighted in the image using colored rectangles and labels.

in the iron), permanent magnet loss in the rotor, friction loss (dry friction, bearing, sealing), windage loss, and the stray loss. The No-load test consisted of driving the motor at a constant speed with zero torque delivered. Because of the gearbox loss and imprecision on the zero torque control, an external torque supplied by the bench was needed to maintain the target speed. This latter torque was measured at the gearbox shaft. The power loss was calculated as the product of the torque measured (at the exit of the gearbox) and the speed in the same measuring point. The copper loss usually accounts for the main part of the electric motor losses, especially at low speeds. In the free-driving condition, the stator current was near zero and so was the copper loss. The gearbox was a single fixed speed with three cylindrical gear stages. The power loss for the gearbox was described in [138], where the power loss was calculated via thermal equilibrium between the latter and the dissipated heat. In general, the power loss via the gearbox consists of load-dependent and no-load dependent losses of the gears and bearings, and the load-independent losses of the gear and lubrication. Decoupling all these loss terms was not possible in a single test with the equipment available, as done in [33, 104]. The experiment data gave the total loss power, which was a function of the speed, neglecting the copper loss (function of the current and thus of the torque) and the gearbox load-dependent loss due to the low torque applied during the test.

6.3 Results

The resistance torques, normalized by the maximum value, for the two powertrains (A, B) are shown in Figure 6.3. Although the nominal values can not be disclosed due to confidentiality concerns, the relative values allow a good comparison in addition to the influence on energy consumption results. The gearbox torque and power maximum values were around 10 Nm and 10 kW, respectively. Powertrain B had a monotone trend and was approximated with a linear piecewise function, a similar behaviour found in other works [83, 84]. The torque resistance of powertrain A was practically equal to B from 0 to 15 km/h and could be considered linear until 100 km/h with a small error. Powertrain A reached the maximum value at 116 km/h and then decreased with the speed.

Normalized resistance power for both powertrains and their difference are shown in Figure 6.4. Power loss of powertrain B had a quadratic relation with the speed due to the torque resistance linearity relation. Although the resistance torque for powertrain A decreased after 116 km/h, the resistance power increased until the maximum value at 221 km/h. Until the

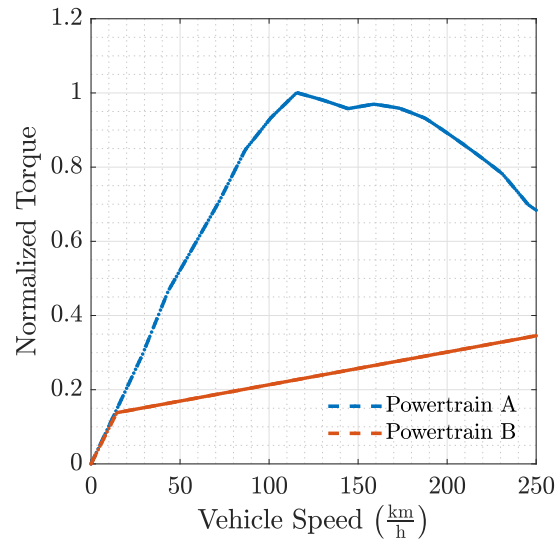


Figure 6.3: Shows the resistance torque vs the wheel speed for both the powertrains. The torque was normalized by its maximum value.

torque decreases to less than linear with speed, the product between the torque and the speed increases (first derivative positive). Normalized consumption was obtained via the vehicle model and the speed profiles described in section 5.4 for powertrains A and B. The vehicle parameters were kept constant for both vehicle models, thus, the mechanical power demand was equal. The front vehicle cross-section did not change, as well as the mass due to the little difference between the architectures, so the focus was just on the free-rolling difference. Figure 6.5 shows the power needed by the vehicle as a function of the speed. The power required by the vehicle was the same for both powertrain models, while the battery power was different due to the different losses and operation points shifting (different efficiency).

The difference between the battery and vehicle power was higher than the power loss through the non-unitary efficiency. This latter difference is shown in Figure 6.6. Thus,

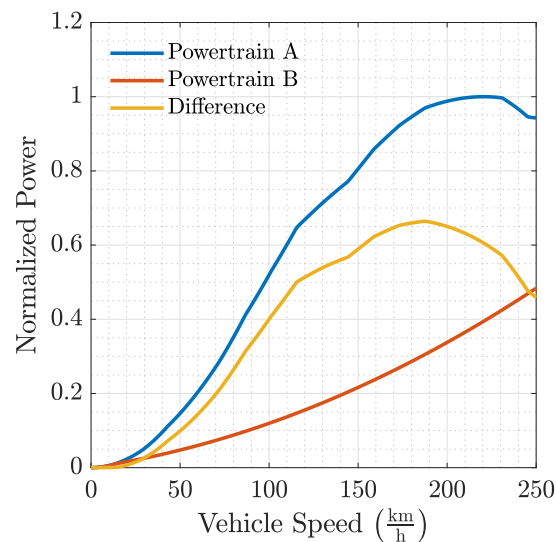


Figure 6.4: Normalized resistance power against the wheel speed for the two powertrains: A (blue line) and B (red line). Also, the difference between the two powertrains was plotted (yellow line).

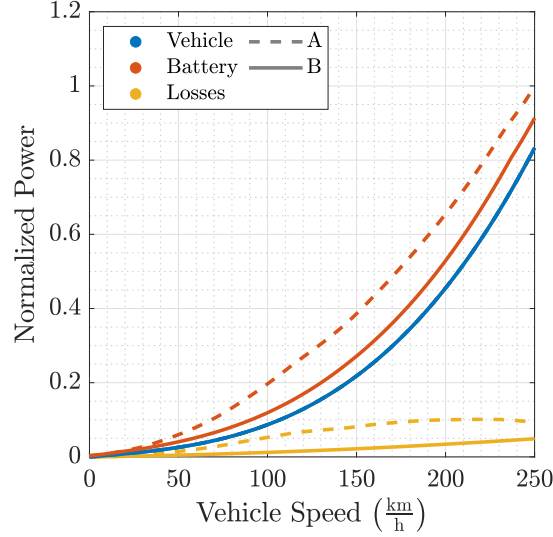


Figure 6.5: Power demand by the vehicle (blue lines), battery (red lines), and no-load losses (yellow lines). The dashed lines refer to the powertrain A, and the continuous lines to the powertrain B.

the no-load losses influenced consumption not only directly, by increasing the mechanical losses, but also indirectly by shifting the powertrain operating points at higher torque during traction and lower values during braking, as shown in Figure 10.1. The speed was constant and given by the speed profile. Varying the operative point meant different levels of efficiency for the powertrain components.

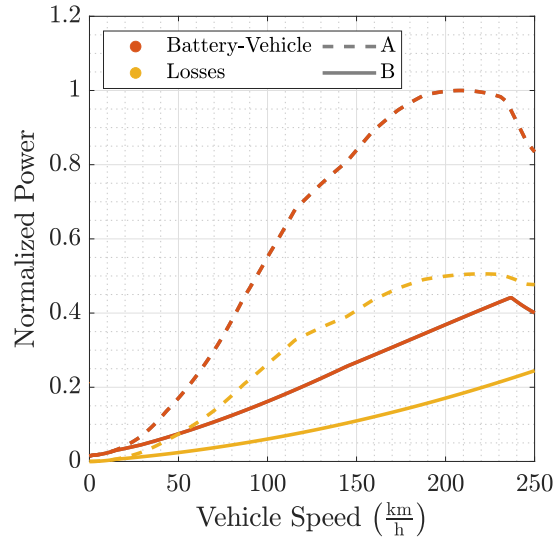


Figure 6.6: Shows the difference between the vehicle and battery power for the A and B units (dashed lines, continuous lines). The power difference is higher than the power loss (yellow lines) due to the non-unitary efficiency.

The results on consumption for the speed profiles were reported in Table 6.1. The mechanical energy was the same for both powertrain models because the vehicle parameters were not changed. The regenerative energy ($\bar{E}_{reg}$), for the same driving cycle, was practically equal for both models. The energy loss by model A was equal to or greater than three times that of model B (299%, 384%) for both the driving cycles (UDSS, WMTC). The

consumption for model A was 42% and 56% higher than B for the UDSS and WMTC speed profiles, respectively.

Table 6.1: Reports the consumption for both the powertrain models (A, B) and different speed profiles (UDSS, WMTC). The specific energy was divided into mechanical, battery, regenerative, net, and loss. All the data are in $(\frac{\text{Wh}}{\text{km}})$.

Driving Cycle	Model	$\bar{E}_{mecc}$	$\bar{E}_{batt}$	$\bar{E}_{reg}$	$\bar{E}_{net}$	$\bar{E}_{Loss}$
UDSS	A	39.17	92.79	4.28	88.51	21.09
	B	39.17	66.96	4.29	62.66	7.04
WMTC	A	56.76	125.4	2.7	122.7	31.9
	B	56.76	81.54	2.8	78.76	8.3

6.4 Power ratios

The losses obtained in the no-load test or free-driving could be approximated with a linear or bi-linear relationship with the speed. From equation 4.39, assuming a constant speed ($a = 0$), it was possible to obtain the mechanical power needed to maintain the vehicle speed. The ratio between the power loss and the vehicle resistance was described in equation 6.1, while the maximum ratio value could be found by solving equation 6.2, and described in equation 6.3.

$$r = \frac{P_{loss}}{P_{mecc}} = \frac{a_l + b_l v}{a_m + b_m v^2} \quad 6.1$$

$$\frac{dr}{dv} = 0 \quad 6.2$$

$$v^* = \frac{-a_l b_m + \sqrt{b_m^2 a_l^2 + b_m a_m b_l^2}}{b_l b_m} \quad 6.3$$

The ratio (r) trend for speed that approached infinity can be obtained as follows:

$$\lim_{v \rightarrow \infty} r(v) = \lim_{v \rightarrow \infty} \frac{a_l + b_l v}{a_m + b_m v^2} = 0 \quad 6.4$$

This result was given by the vehicle resistance force quadratic dependency on speed, while the power loss was linear with speed. Thus, at higher speeds, the influence of no-load loss will be lower. The ratio for the motorcycle model against speed is shown in Figure 6.7, for the model A (Figure 6.7a), and the model B (Figure 6.7b).

The ratio (r) increased with velocity until the maximum, described in equation 6.3, then tended to zero as suggested by equation 6.4. The highest value was almost 64%, and 20% for models A and B, respectively. The former value was obtained at a speed of 86 km/h, and the latter value at a speed of 27 km/h. The ratio between the vehicle and battery power should be ideally one (no losses and unitary efficiency). While this latter ratio increased monotonically for model B, for model A, from a speed of 18 to 125 km/h, the ratio was almost constant with a range from 42% to 50%.

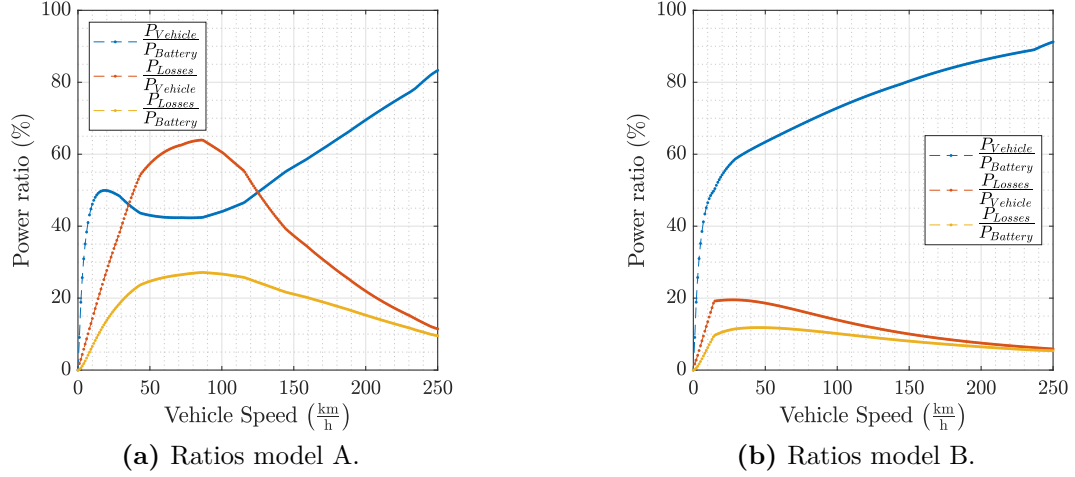


Figure 6.7: Shows the ratio between the vehicle and battery power (blue line), the loss and vehicle power ratio (red line), and the loss and battery power ratio (yellow line).

6.5 Conclusion

According to the data, the resistance torque was practically linear with the speed between 0 and 100 km/h in the case of powertrain A. The powertrain A loss, at high speed, started to decrease, and the causes were not fully understood due to ancillaries and magnetic interactions. The increment in consumption due to the higher resistance torque was less significant compared to the increment given by the operative point shifting. Indeed, the sum of the mechanical and loss energy was lower than the battery energy, as visible in Figure 6.6. Vice versa, the regenerative energy was not affected by the no-load loss, and both the powertrains obtained almost the same value. This result could be explained by the low braking power needed by the cycle (maximum deceleration value was -2 m/s^2), and at low speeds, the resistance power did not differ too much between the two powertrains, as shown in Figure 6.4.

The consumption on UDSS was 88.51 Wh/km for model A and 62.66 Wh/km (-29.2%) for model B, and on WMTC was 122.7 and 78.76 Wh/km (-35.8%) for model A and B, respectively. The difference in net energy between the two powertrains was 25.85 and 43.94 Wh/km for the UDSS and WMTC driving cycles, respectively. This latter difference was higher than the energy loss difference, which was 14.05 (UDSS) and 23.6 (WMTC) Wh/km, due to the efficiency of the final drive, motor, etc. The powertrain A and B efficiency, calculated as the ratio between the mechanical energy and the net energy, was 44.2% and 62.57% for the UDSS speed profile, 46.2% and 72.1% for the WMTC speed profile.

The vehicle parameters were kept constant through the simulations because the front cross-section area and drag coefficient were considered independent from the powertrain model, and the vehicle mass was also not influenced significantly by the powertrain (electric machine and inverter). This way, it was also possible to focus the research only on the difference in the reduction stage. At the low speed, the tire rolling resistance was more important, then the loss increased with speed more than the aerodynamic resistance, and thus r increased at its maximum as described in equation 6.3. At high speed, the no-load loss became less important (Figure 6.7) because the denominator in equation 6.1 grew more than the numerator.

The powertrain investigated will be less influenced by consumption by the no-load loss when driving a motorcycle on a track because the resistance load accounts for all the energy

needed.

The powertrain A has a great impact on consumption for light motorcycles (low tire resistance rolling) and speed range between 40 and 120 km/h. This latter speed range is common for city and highway motorcycle riding.

The free-driving losses were experimentally characterized for two different powertrains. Their behavior can be described just by the speed, neglecting the load-dependent loss, which was very low in this situation. No-load loss influence on consumption was analyzed analytically (constant speed) and numerically via a motorcycle model and two speed profiles (UDDS, WMTC). The difference in consumption was significant between the two powertrains, with a decrement for powertrain B of -29.2% and -35.8% for UDDS and WMTC, respectively. At high speeds, when aerodynamic load resistance is the main reason for consumption, the free-driving loss is less important. By these considerations, a non-high-performance motorcycle would benefit from a more oriented high-torque machine, which needs fewer reduction stages or none at all.

The high-torque machine, typically, has a lower power density; thus, keeping the same power could lead to a mass and volume increment of the powertrain, and as a consequence, an increase in consumption due to the rolling resistance and loss of the benefits. Because the free-driving loss is not load dependent, their increased relative consumption on light vehicles and in mid-speed range value (40 - 120 km/h) is more pronounced.

The results highlight an influence on riding range reduction of 23.8% and 26%, 11.2% and 10.5% for powertrains A and B, respectively, according to the simulated driving cycles (UDDS and WMTC). In conclusion, an experimental evaluation of no-load loss was done on two powertrains, and qualitative and quantitative impacts on consumption for electric motorcycles were found.

7. VEHICLE OPTIMIZATION

7.1 All-wheel regenerative motorcycles

7.1.1 Vehicle architecture and brake blending

The Implementation of a front wheel-hub integrated motor on electric motorcycles was studied in previous work for the scope of energy efficiency [22, 200], and handling improvement [176]. The possibility of applying traction and braking forces by the front wheel allowed for higher control of the vehicle, improving stabilization, different handling in curves, and a safer allocation of adherence coefficients. The transfer of power to the front wheel could be realized via many solutions such as a hydraulic actuator, one single motor (installed on the main frame) that drives both the wheels via mechanical linkages (chain, shaft, gears, etc.), and an integrated front wheel motor (hub or rim). This latter solution avoids transmission power loss, saves on-board vehicle space, and allows independent drive control. A ring motor integrated into the front wheel rim could be implemented to fit inside the front wheel volume (short axial length and high inner and outer diameter) to minimize the weight [45]. Integrated electric motors also introduce technical issues like more difficult thermal management, more exposure to dirt and dust, and a higher possibility of being damaged by a crash or impact. In addition, an increment of unsprung masses, and wheel inertia (higher gyroscope effect on the front steer frame) could lead to manoeuvring difficulties and thus compensation via modifying the caster angle or other geometry motorcycle aspect (normal trail, front fork offset, etc) might be considered such as an increment in price and vehicle maintenance. The effectiveness of regenerative braking for electric vehicles was already investigated [99], and its contribution to reducing consumption was found to not be negligible, especially for dynamic driving cycles, like urban driving with many starts and stops, and with maximum braking power compatible with the power capability regenerative braking system. For electric motorcycles, the introduction of a front motor might have a high impact on reducing consumption, and due to the lack of studies (few studies and few driving cycles), only the aspect of energy recovery was investigated in this section. For the analysis of the vehicle architectures and an estimation of the consumption, a simplified motorcycle model was developed. The simulation environment, MATLAB/Simulink, was utilized for this scope. The vehicle model, based on in-plane vehicle dynamics (1 DOF), was comprehensive of the

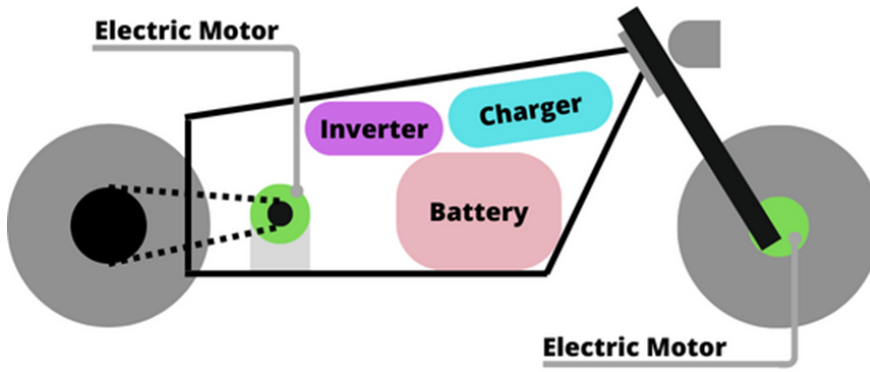


Figure 7.1: A simple scheme of two-wheel driven electric motorcycles. The rear motor torque is supplied to the rear wheel via a chain transmission, while the front motor is implemented directly in the front wheel hub.

mechanical and electrical system (powertrain), the rider (speed profiles controller), the environment (road grades), and the braking strategy. The two configurations (RWR, 2WR) shared the same component for the rear wheel powertrain, which consists of a permanent magnet synchronous machine (PMSM), transmission (single gear ratio), final chain transmission, and battery. For the two-wheel regenerative (2WR) architecture, an additional wheel hub motor was implemented in the front wheel, increasing the vehicle mass by 15 kg in this configuration. The total mass, including the rider mass, was 370 kg for the rear wheel regenerative (RWR) architecture. A schematic representation of the 2WR architecture is shown in Figure 7.1. All the vehicle parameters for the calculation of driving resistance were kept constant for the whole simulation and based on literature values. The product of the front cross-sectional area and drag coefficient is 0,32, and the rolling coefficient is 0,013. The vehicle model neglects many aspects like the tire slip, the influence of suspension, the lateral dynamics, and other aspects that might influence the consumption; the efficiency of the powertrain group is based on a typical PMSM machine, a technology typically suitable for motorcycle application, Table 7.1 summarizes the main vehicle and powertrain parameters. Despite these limitations, a control on the adhesion longitudinal coefficient and wheelie was implemented to avoid possible unphysical phenomena. The two speed profiles are shown in Figure 7.2. The first one is the WMTC speed profiles while the second one was obtained by processing of naturalistic riding in a mixed urban and rural trip (Firenze-Bologna on open roads) using an electric motorcycle whose size is comparable to the simulated one; therefore, such real-world data are considered a typical case study for the vehicle class under analysis. The WMTC part 2, class 3, subclass 2 was chosen because it is the standard for test homologation of motorcycles with a maximum vehicle speed greater than or equal to 140 km/h [207]. The average driving speed is 58.8 km/h (WMTC) and 48.6 km/h (experimental), and the maximum speed is 94.9 km/h (WMTC) and 133 km/h for the other speed profile. The two cycles have a standard deviation of acceleration value of 0.68 m/s² (WMTC) and 0.76 m/s² (experimental). Finally, the WMTC has a difference in altitude of zero meters, while the other speed profile has a maximum altitude variation of 926 meters. Figure 7.3a shows the motorcycle path, comprehensive of altitude, for a micro-trip of the data, while Figure 7.3b shows the GG plot. The GG diagram is the plot of the longitudinal acceleration vs the lateral acceleration.

Electric motors can also work as a generator to recover the vehicle's kinetic energy during braking manoeuvres. The two main aspects that influence the braking performance in the simplified model were the braking distribution (ρ) and the brake-blending strategy. These latter variables describe the braking force axle repartition and the brake axle force

Table 7.1: Main Model parameters.

Symbol	Value	Unit	Description
M_{RWR}	370	kg	Vehicle and rider mass RWR architecture
M_{2WR}	385	kg	Vehicle and rider mass R2WR architecture
c_{rr}	0.013	-	Rolling resistance coefficient
A_{f}	0.64	m ²	Front cross-section area
C_{d}	0.5	-	Drag coefficient
w_{b}	1.6	m	Wheelbase
a_1	0.83	m	CoG distance from the front wheel ground contact point
h	0.58	m	CoG height
r_{w}^{r}	0.319	m	Rear wheel radius
r_{w}^{f}	0.321	m	Front wheel radius
τ^{r}	8.6	-	Gear ratio (rear electric machine to rear wheel)
τ^{f}	8.6	-	Gear ratio (front electric machine to front wheel)
C_{b}	22.5	kW h	Battery capacity
V_{b}	300	V	Battery voltage
$P_{\text{max}}^{\text{r}}$	96	kW	Rear electric machine max power
$P_{\text{max}}^{\text{f}}$	12	kW	Front electric machine max power

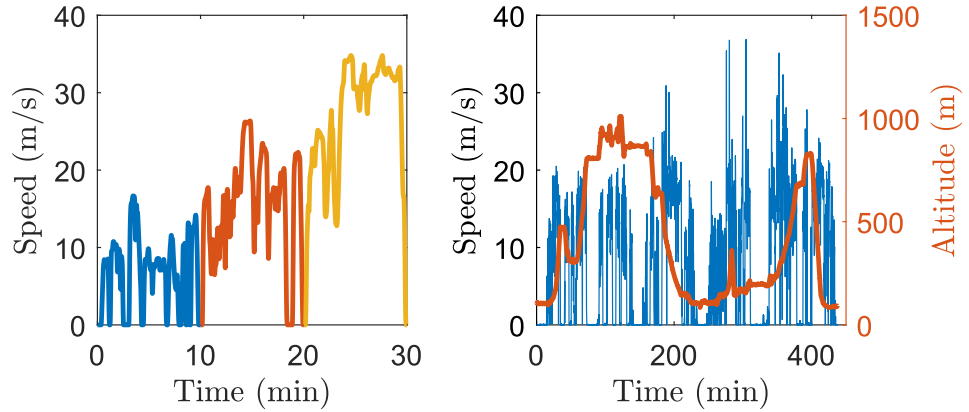


Figure 7.2: Shows the vehicle class 3 WMTC speed profile on the left subplot. Only part 2 was used for the analysis (colored in orange). On the right subplot are displayed the speed and altitude signals recorded during a motorcycle trip and used for the creation of the experimental driving cycle.

splitting between the friction brakes and the regenerative brakes, respectively. The braking distribution (ρ) was defined slight different as in section 4.6 , Equation 4.113, resulting as follows:

$$\rho = \frac{X_{\text{r}}}{X_{\text{r}} + X_{\text{f}}} \quad 7.1$$

where X_{r} is the rear axle brake force, and X_{f} is the front axle brake force. The braking ratios (ρ) range from 0 (no rear brake) to 1 (only rear brake). The braking distribution was kept constant from the beginning to the end of the simulations, but it was changed between different runs, and it belongs to the following set: $\rho = \{0, 0.25, 0.5, 0.75, 1\}$. In order to increase the energy regeneration, a serial control strategy was implemented for each axle [237], albeit it means a worse and less safe adherence coefficient allocation with potential issues at high deceleration [218]. This latter strategy first splits the braking torque request between

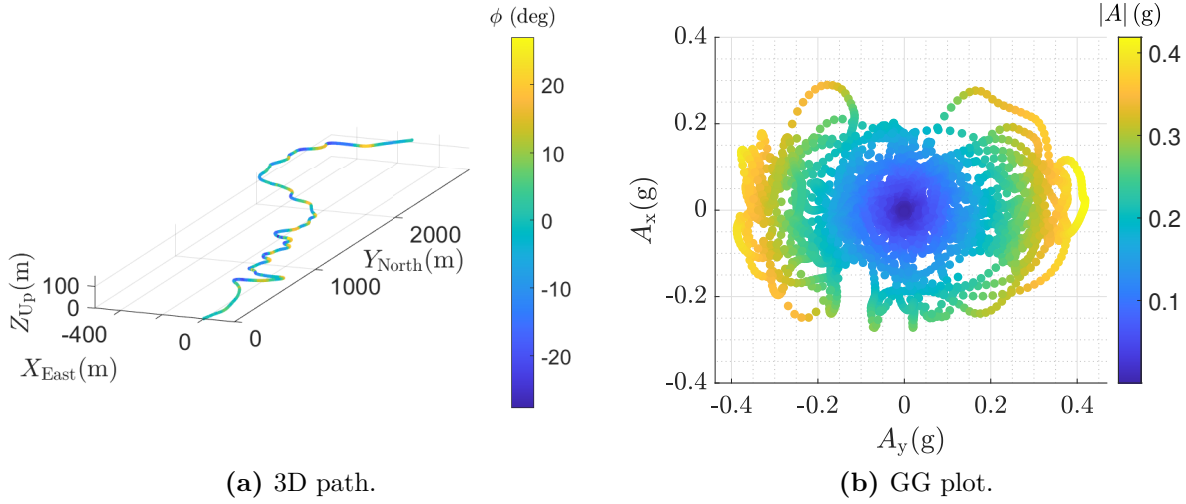


Figure 7.3: a) shows the partial 3D path of the riding, the line is colored by the roll angle; b) Illustrates the GG plot, on the x-axis the lateral acceleration and the y-axis the longitudinal acceleration, dots are colored by the acceleration norm.

the two axes, then aims to demand the maximum regenerative torque allowed by the motor, and then the remaining braking torque request is added by the frictional/dissipative brakes as done in previous work [319]. The feasibility of the braking system or the possibility of implementation was not considered in this work, but the focus was on the outcomes in terms of energy and regenerative braking. The brake-blending strategy, for the RWR architecture, was defined by Equation 7.2, while the graphic representation of the logic for the 2WR architecture is shown in Figure 7.4 for a braking ratio equals to 0.5, so same braking force is applied on both the wheels.

$$F_{\text{brk}} = \begin{cases} F_{\text{reg}}, & F_{\text{brk,requested}} \leq F_{\text{reg,max}} \\ F_{\text{reg,max}} + F_{\text{mech}}, & F_{\text{brk,requested}} > F_{\text{reg,max}} \end{cases} \quad 7.2$$

The action of braking was implemented via blending the two types of braking (regenerative and dissipative), independently of the rider's actions. The brake lever feedback of a hypothetical rider will not be affected during the braking maneuvers because the rider's brake demand was guaranteed with different combinations of the brakes without changing the output (total brake force). Despite the lower front motor power compared to the rear motor, it is still enough to cover all the requested braking powers. These latter powers are shown in Figure 7.5a for the WMTC speed profile and the 2WR motorcycle, and in Figure 7.5b for the experimental data. Finally, for both architectures, the torque needed for the traction was supplied only by the rear motor for simplicity, given the aim of studying the braking energy and regeneration. Multiple vehicle simulations evaluated how the different powertrains, driving cycles, and braking parameters influence consumption. An investigation of the powertrain components was conducted by switching from the two architectures (RWR and 2WR), changing the braking distribution value (for a total of five values), and changing the drive profile (WMTC, experimental). In addition, an analysis of the road slope influence on operation point and energy flow was conducted, adding altitude profiles at the WMTC speed profile to evaluate the influence of the road slope on consumption [27]. The altitude profiles were obtained considering a constant road slope angle (α) for the whole distance traveled by the vehicle. This latter variable ranges from minus five to five degrees with incremental steps of half a degree. The modified speed profiles are shown in Figure 7.6 The net energy, average motor efficiency, and equivalent energy were used for each simulation

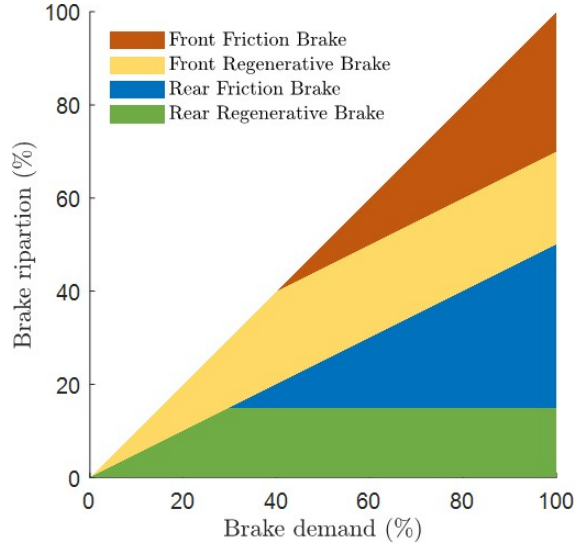


Figure 7.4: shows the brake serial control strategy for a two-wheel regenerative electric motorcycle ($\rho = 0.5$). Highlighted areas represent the cumulative braking force for each type of brake device.

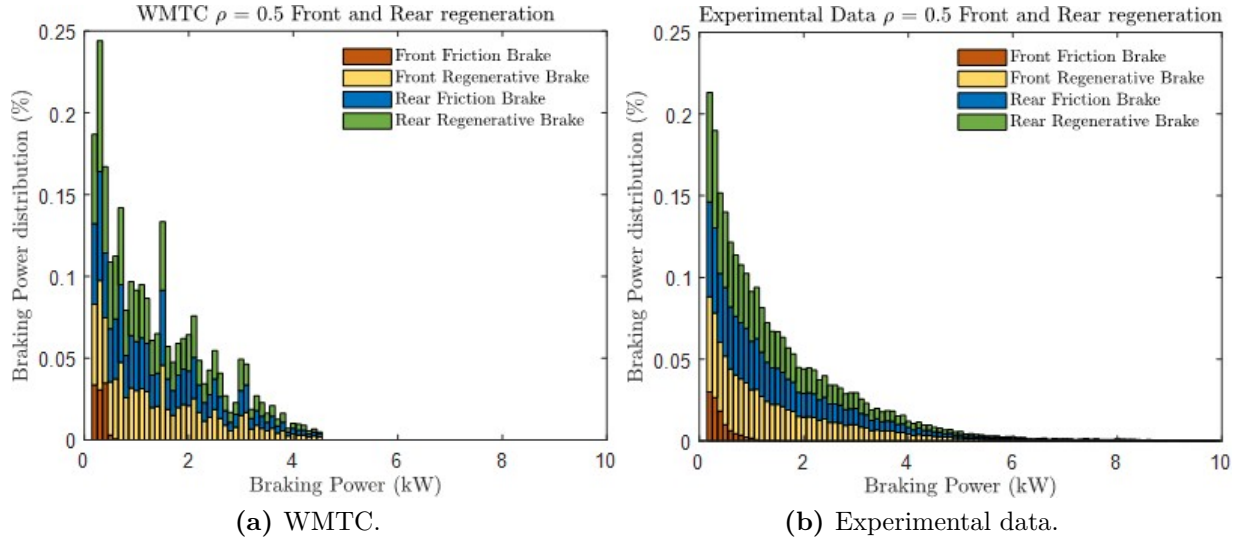


Figure 7.5: **a)** shows the braking power distribution for the WMTC speed profile; **b)** for the experimental speed profile collected with an electric motorcycle. Both the plots refer to the two wheels regenerative motorcycle for a braking repartition equal to 0,5.

to compare the different vehicle configurations and speed profile results. Net Energy was defined as the difference between supplied battery energy and the regeneration energy, at the battery, normalized by the distance traveled by the vehicle, as described as follows:

$$\bar{E} = \frac{E_{b,in} - E_{b,out}}{distance} \quad 7.3$$

Average motor efficiency was defined as the mean efficiency of the electric motors (only rear, for a fair comparison between architectures) achieved during all the operations (traction and braking), using a look-up table depending on RPM and torque, equivalent to a typical PMSM efficiency. Equivalent energy is the net energy minus the normalized potential energy by the distance, and it is the energy spent by the vehicle considering a zero net altitude, but with a different efficiency of the powertrain. With these parameters was possible to compare results

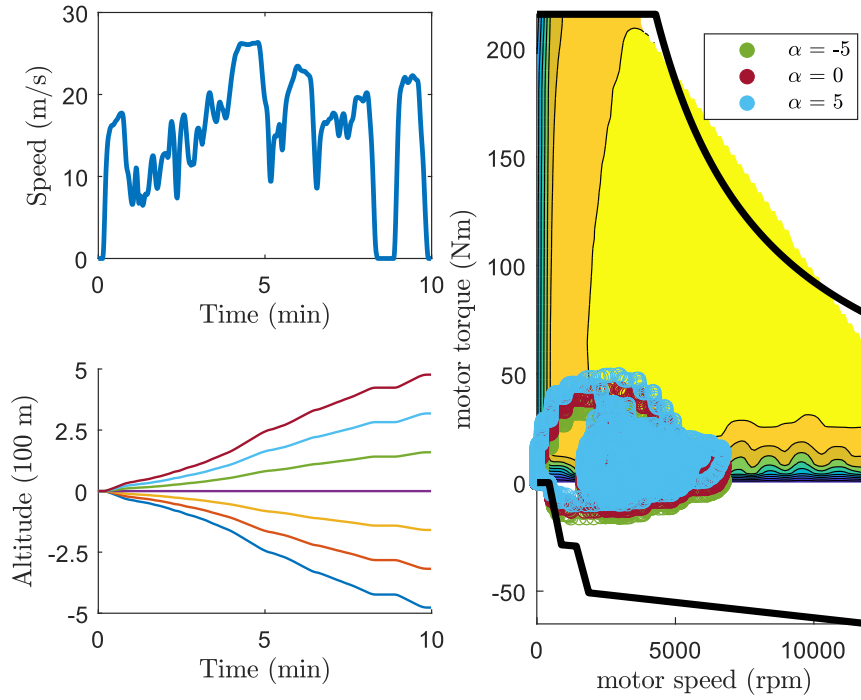


Figure 7.6: In the top right subplot is plotted the WMTC speed vs. time signal. Different altitude profiles are shown for different constant road slope values in the bottom left subplot. On the right subplot, the operation points for three different road slope angles are shown.

obtained by different boundary and initial conditions, input data, and vehicle configurations.

7.1.2 Results

The results obtained for the two driving cycles (WMTC, experimental) and the architectures (RWR, 2WR) are shown in Figure 7.7. The RWR configuration had a normalized energy request of 62.6 Wh/km and 63.9 Wh/km for the WMTC and experimental profiles, respectively. The 2WR energy demand for the same cycle list was 63.8 Wh/km and 66 Wh/km. When the braking distribution was equal to one, the lowest consumptions were obtained for all the vehicle architectures (RWR, 2WR) and speed profiles (WMTC, experimental ride). The minimum value of the 2WR was always higher than the minimum value of the RWR configuration. The maximum value for the RWR configuration was always obtained for ρ equal to zero (no regeneration at all). The 2WR maximum was obtained for ρ equal to 0.25 in both cycles ($\rho = 0$ means only front regeneration). The RWR consumption ranges from 54.1 to 62.7 Wh/km and from 48.4 to 63.8 Wh/km for the WMTC and experimental profiles, respectively. The 2WR configuration ranges from 54.9 to 56.3 Wh/km (WMTC profile) and 50.5 to 52.8 Wh/km (experimental profile).

The energy ratio, described as the ratio between the regenerated energy and the delivered energy, is shown in Figure 7.8. The minimum ratio value (0%) was obtained for the RWR in the case of no regeneration ($\rho = 0$) independently of the driving cycle. The 2WR configuration has a minimum of 11.7% (WMTC profile) and a maximum of 23.6% (experimental profile), while the maximum ratio was 23.7% for the RWR-WMTC combination.

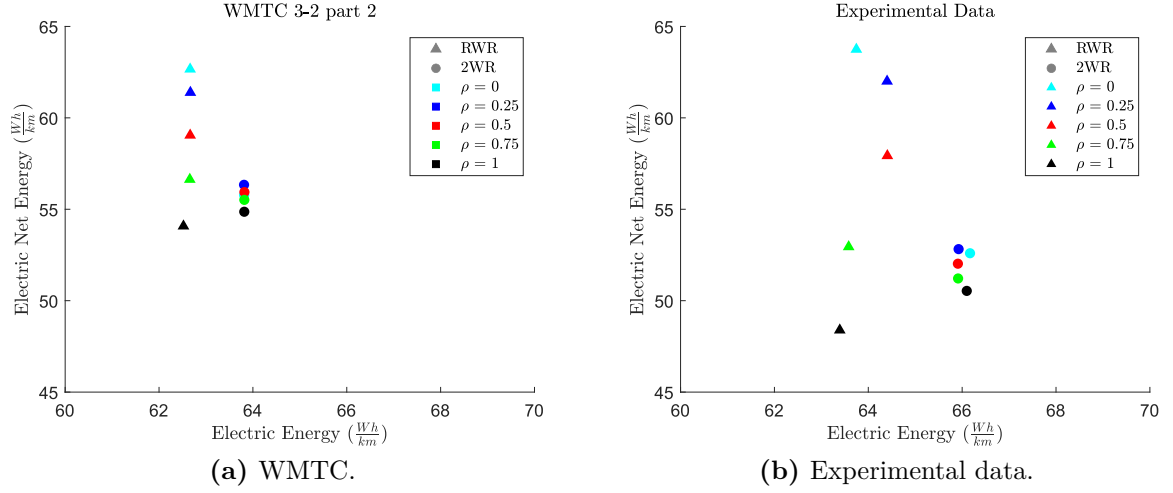


Figure 7.7: Shows the results for the speed profiles, WMTC (a) and the experimental data (b), on the left and right, respectively. The geometric dot shape (triangle, circle) means the vehicle configuration (RWR, 2WR). Different colors mean different braking distribution values (see the legend for details).

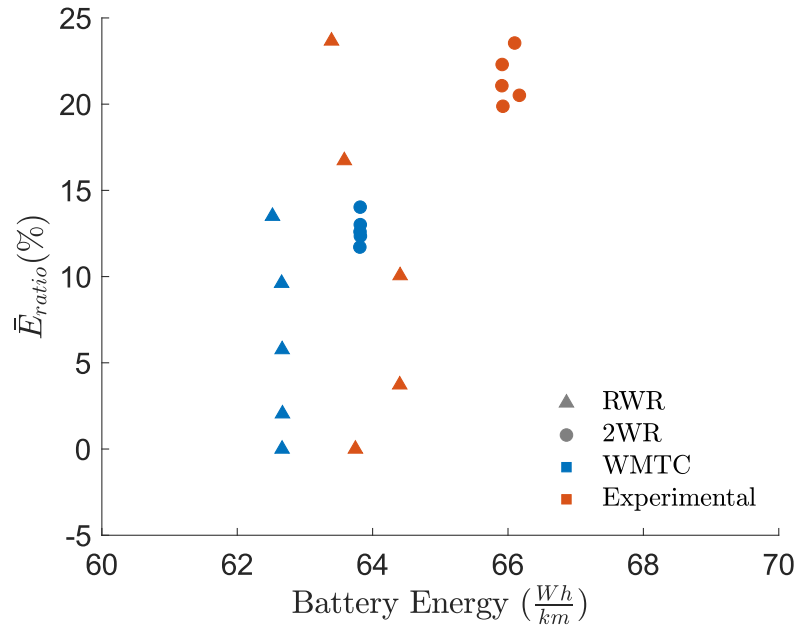


Figure 7.8: Shows the energy ratio for different configurations and speed profiles. The geometric dot shape (triangle, circle) means the vehicle architecture configurations (RWR, 2WR), while the dot color (blue, orange) means the speed profile (WMTC, experimental).

An analysis of the road slope influence on consumption was performed by adding altitude profiles at the WMTC speed profiles (constant road slopes, see Figure 7.6 for some examples). The net energy results for the two configurations are shown in Figure 7.9, RWR on the left subplot and 2WR on the right subplot.

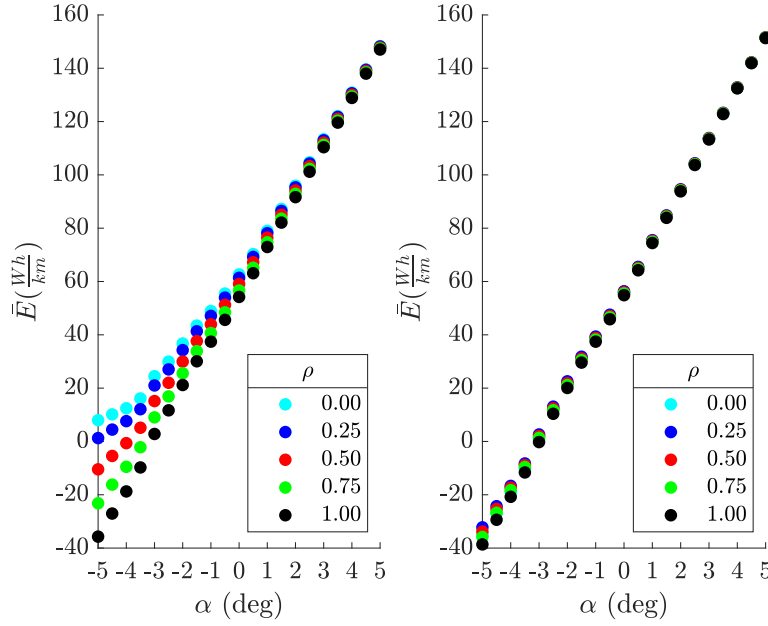


Figure 7.9: Shows the net energy for the RWR on the left subplot and the 2WR on the right subplot for five values of the braking distribution (ρ).

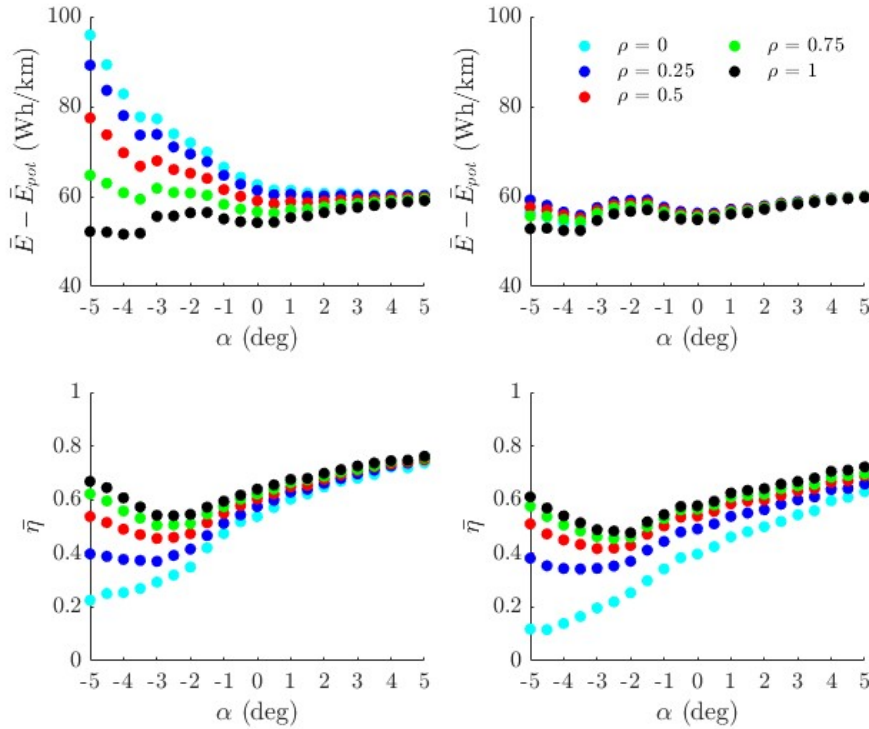


Figure 7.10: The two top subplots show the net energy minus the potential energy normalized by the distance for the two vehicle configurations (RWR on the left and 2WR on the right). In the two bottom subplots, the average rear motor efficiency is displayed.

For positive road slope values (uphill direction), the net energy was less influenced by the braking distribution value. In the downhill direction (negative alpha values), variation of ρ affects the net energy, and in the case of 2WR, it was always negative for all the values. At

minus five degrees, for the WMTC profile, the net energy range was 43.7 Wh/km (RWR) and 5.1 Wh/km (2WR). The maximum consumption was 148.3 (RWR) and 151.6 Wh/km (2WR) at α equal to five degrees and changing the braking distribution, reducing consumption by 1.3 and 0.3 Wh/km (RWR, 2WR) at maximum. With the addition of the road slope, there is also an additional demand for energy (potential energy) and so on, for consumption. Thus, to evaluate the architecture performance at the net energy, the normalized potential energy was subtracted from it. Figure 7.10 for the modified WMTC profile displays this latter new energy and the average rear motor efficiency. The higher the road angle, and higher the average rear motor efficiency for all the configurations and braking distribution values. Furthermore, looking at the RWR results, the difference between the net and normalized potential energy decreased for ρ equal to 0 and 0.25 and increased for the other values. While for the 2WR with positive road grades, the increment was always bigger than with zero road angle. The efficiency of the rear motor increased with positive angles in both vehicle configurations, while it had a non-monotonic trend for negative α values (increasing and decreasing).

7.1.3 Discussion and conclusion

The 2WR had always had the highest energy demand (63.8 and 66 Wh/km) in both cycles (WMTC, experimental) than the RWR, due to the mass increment given by the front motor. The RWR had the lowest consumption (54.1, 48.4 Wh/km) in each driving cycle when was equal to one (only rear braking force). Setting $\rho = 0$ could also be seen, energetically speaking, as a strategy where the regenerative rear brake is saturated, and then the other braking power is supplied by frictional brakes (front or rear). The worst consumption results (56.3, 52.8 Wh/km) for the 2WR were obtained for ρ equal to 0.25, but they were lower than the second best result of the RWR (at $\rho = 0.75$). The 2WR with $\rho = 0$ (only front braking regeneration) performed a little better than 0.25 braking distribution. With ρ equal to one, the 2WR vehicle had higher consumption than the RWR with the same braking distribution value, due to the energy losses induced by the mass increment, such as the tire rolling resistance moment and the non-ideal powertrain efficiency (impossibility of recovering all the energy). This result was still the better result of the 2WR even if the front motor does not recover energy. The RWR consumption was reduced, compared to the non-regenerative case (RWR, $\rho = 0$) of 13.6% (WMTC, $\rho = 1$) and 24.1% (experimental, $\rho = 1$). The 2WR reductions were of 12.4% (WMTC) and 21% (experimental). While the worst results were 2% (WMTC, $\rho = 0.25$) and 2.7% (experimental, $\rho = 0.25$) for the RWR. The 2WR architecture obtained 10.1% (WMTC, $\rho = 0.25$) and 17.14% (experimental, $\rho = 0.25$) as worst consumption reductions, which were more than three times bigger than the RWR worst results. The lower energy recovery results on WMTC than the experimental profile were related to the lower energy dissipated via braking, rather than air drag and rolling resistance, so the braking regeneration had less consumption due to the speed profile nature. Looking at the energy ratio, the conclusions are the same as those made for the net energy; in fact, the energy ratio is equal to one minus the ratio between the net energy and the supplied energy. The final energy consumption of the 2WR was less sensitive to the braking distribution in comparison with the RWR; due to the increased mass, however, the absolute value was comparable or higher. Considering braking distribution with the prevalence on the front axle, the potential energy consumption reduction due to regeneration was estimated to be remarkable, from 2.7% (experimental profile, RWR, $\rho = 0.25$) to 17.1% (experimental, 2WR, $\rho = 0.25$). Therefore, for these speed profiles (moderate deceleration, coherently with naturalistic riding on open roads, and with WMTC values) a solution with only a rear braking regeneration is assessed to be the optimal solution for energy regeneration and consumption

but it might be not for a safety allocation of the longitudinal adherence coefficient (road slippery condition or influence the ABS activation).

An increment of the net energy by adding a positive road slope was trivial because, for the same speed profile, it was added a request for more energy (potential energy) was added. As well as a decrement with negative α values. Interesting was the relative increment/decrement of net energy (+136%/-87.3%, $\alpha = 5/-5$), which was more than the potential energy itself because of the non-unitary efficiency of the powertrain. With positive slope angles, the influence of the braking distribution on consumption was negligible for both architectures because of the same deceleration (same speed profile). The braking force was mainly supplied by the force of gravity component parallel to the road (decrement of the braking force). A lower longitudinal road angle meant a higher difference in net energy for different ρ , especially for the RWR configuration. The average rear motor efficiency (Figure 7.10) increased with the increment of positive α values, thus the motor worked at an overall higher average efficiency (higher in traction and lower in braking) than the zero-altitude profile. Instead, with a negative road slope, the efficiency decreases until a local minimum between -2 and -3 degrees and then increases again due to the limit of braking regeneration (motor cut-off). Positive α values reduced the ρ independency on the equivalent energy because the tire forces were mainly positive (traction). For a certain value of α or bigger, there are no braking tire forces at all, thus the equivalent energy convergence to a unique value, independently of the ρ variable. Vice versa for negative road slope values, the braking tire forces increase and ρ influences strongly the results, especially for the RWR configuration. Even if the average rear motor efficiency had similar behavior increases in both vehicle configurations (Figure 7.10, two bottom subplots), the equivalent energy (Figure 7.10, two top subplots) and net energy (Figure 7.9) were less affected for 2WR vehicle by the choice of ρ because of the front motor efficiency increment.

In this section, the influence on the consumption of two fully electric motorcycle architectures was investigated via two different speed profiles, five braking distribution values, and a serial control braking strategy. In addition, the influence of the road slope was analyzed by adding altitude profiles at the WMTC speed profile. Results suggested that the rear wheel regenerative (RWR) architecture is preferable (less consumption, much simpler, and cheaper) if it is possible to apply a logic where the rear regenerative torque is prioritized ($\rho = 1$). The 2WR benefit of an almost braking distribution independence on energy reduction. This latter configuration could be better in situations where high decelerations and high adhesion coefficients are required, thus, the investigation via a harsh driving cycle could be worthwhile. The energy dissipated by the brakes (regenerative and frictional) was the same for the same cycle and vehicle configuration. Thus, only rear wheel regeneration must be preferred with low deceleration and not harsh applications such as mopeds, due to the lower vehicle mass, complexity, and cost as found by the other study [200]. The 2WR, despite the complexity increment, could be a solution for sport driving cycles because the ρ independence allows it to regenerate with the front or rear wheel proportional to the braking request. Furthermore, two motors could allow for the optimization of the traction phases that were not studied in this work. On the other hand, adding mass and moment of inertia to the front assembly influences the vehicle handling, so a different setup (caster angle, normal trail, etc.) could be necessary for this type of vehicle. An analysis of the road slope was conducted, even with all the limitations of adding in retrospect altitude profile on a speed profile. The results showed that consumption obviously increased (uphill direction) and decreased (downhill direction), but the road slope also had an influence on the operative points. The efficiency (not unitary) of the powertrain, even for an altitude profile with zero potential energy, implies an increment of consumption, and neglecting the road slope at all is a simplification, especially for the RWR configuration. The road slope acts by transferring the weight from one axle to

the other (uphill or downhill direction), shifting the braking force consequently, so a 2WR configuration could be preferable to avoid wheel locking. More detailed studies for harsh cases and more architectures, considering the legal constraint, should be made to clarify if the increment of mass and complexity fulfills the energy reduction; otherwise is better to invest in vehicle development of other solutions such as mass reduction, tire improvement, and powertrain efficiency optimization.

7.2 Powertrain Optimization

7.2.1 Optimization Problem

An optimization problem is made of three main factors: the cost or objective function (J), the decision variables (x_s), and the constraints. The objective is a function application to the decision variables, and the algorithm or optimizer aims to find the optimal solution (x^*) that minimizes the function. This latter problem can be expressed as follows:

$$\begin{aligned} \min_{x_1, x_2, \dots, x_n} \quad & J(x_1, x_2, \dots, x_n) \\ \text{s.t.} \quad & \text{Constraints} \end{aligned}$$

Furthermore, the decision variables can be bounded by values and constraints. When we are interested in a multi-objective problem, the optimal solution might be more than one, especially if the objectives conflict. Thus, the minimization of one cost function deters at least one of the others. When a solution can not improve any objective despite increasing the other objectives, a trade-off solution is found. These latter solutions form the Pareto optimal front. During the optimization, we aim to achieve one of the Pareto solutions. For better understanding, the following example is proposed:

$$\begin{aligned} J_1 &= \frac{1}{x_1 + x_2} \\ J_2 &= x_1 + x_2 \end{aligned}$$

where x_1 and x_2 are the decision variables, J_1 and J_2 are the cost functions. The decision variables are bounded in a subset of the real numbers, whereby

$$x_1, x_2 \in [0, 4]$$

The Pareto front can be found by minimizing a single cost function expressed as the sum of the two cost functions as follows:

$$\min_{x_1, x_2} J = J_1 + J_2$$

The solutions to the problem are shown in Figure 7.11, and can be found through optimization algorithms like the *paretosearch* function on the MATLAB environment.

7.2.2 Vehicle Optimization investigation

To better understand the powertrain optimization, a simplified problem is written, albeit it still gives hints on the powertrain puzzle design. The vehicle mass (m) is defined in Equation 7.4 as the sum of the rider mass (m_r), the glider mass (m_0), the motor mass (m_m), and the battery size (C_b) divided by the battery energy density (ρ_b) as follows:

$$m = m_r + m_0 + k_A k_R^2 m_m + \frac{C_b}{\rho_b} \quad 7.4$$

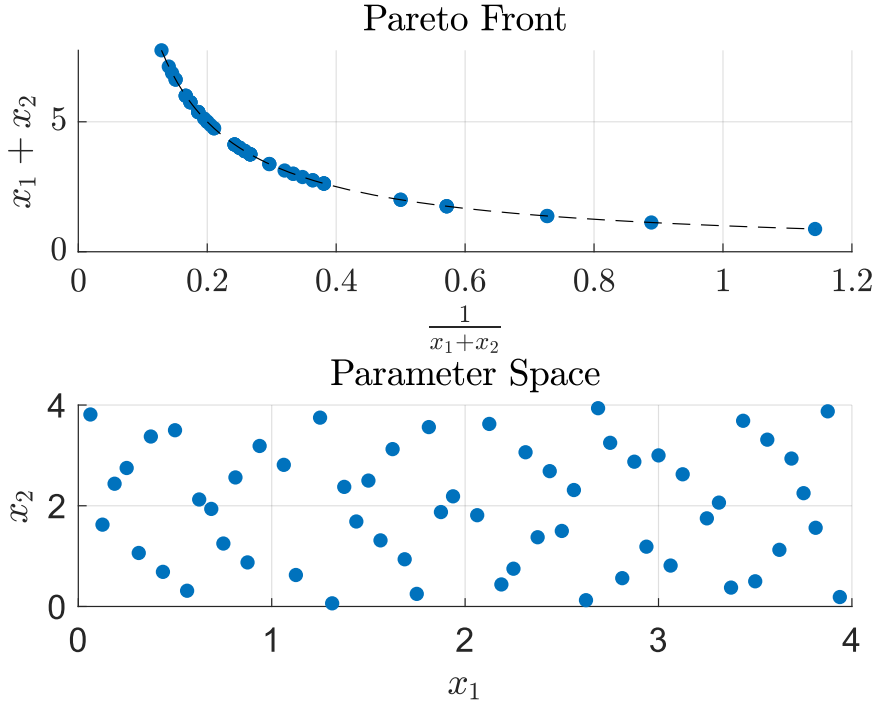


Figure 7.11: Example of multi-objective optimization. The top plot shows the two objective functions (discrete values) and the Pareto front (dashed line). The bottom plot shows the parameter space for the two variables (x_1, x_2) .

where k_A is the length axial scaling factor, and k_R is the radius scaling factor. These latter factors were introduced in section 2.5.3. Using a one degree in plane vehicle model the vehicle power required (P_v) can be determined by equations 7.5, and as shown from the analysis in section 5.2 can be approximated with only the positive acceleration intervals.

$$P_v = \left(\frac{1}{2} \rho_{\text{air}} C_d A v^2 + m(c_{rr} + a^+) \right) \cdot v \quad 7.5$$

Where ρ_{air} is the air density, C_d the drag coefficient, A the cross-section area, v the longitudinal speed, and c_{rr} the rolling resistance coefficient. Even with a weaker, but still moderate correlation, the braking power is correlated to the characteristic equation, and thus the recoverable energy (P_r) can be expressed as the first approximation as a fraction of P_v , via the regenerative braking factor (r) as follows:

$$P_r = r P_v \quad 7.6$$

The net power or the battery power (P_b) can be calculated as the difference between the vehicle power and the recovered power, divided by the gearbox efficiency (η_{gb}), battery efficiency (η_b), and inverter efficiency (η_{inv}).

$$P_b = (1 - r) \frac{P_v}{\eta_{gb} \eta_b \eta_{inv} \eta_m} \quad 7.7$$

The energy battery needed for a cycle can be calculated via integration over time of the battery power leading a the following equations:

$$E_b = \int_0^T P_b dt = \sum_0^T P_{b,i} \cdot dt \quad 7.8$$

The battery capacity (C_b) must be at least equal to the energy needed to run a full cycle, and so is constrained by the equation 7.10 to within its operational range through the coefficients of minimum and maximum state of charge $\xi_{\min}$ and $\xi_{\max}$. Thus, the battery is not fully charged or discharged to prevent faster deterioration and aging.

$$D = \int_0^T v dt \quad 7.9$$

$$E_b \leq C_b(\xi_{\max} - \xi_{\min}) \quad 7.10$$

The power and torque required must be equal to or lower than the maximum reference power ($\bar{P}_{\max}$) and the maximum reference motor torque ($\bar{T}_{\max}$), scaled by the scaling factor introduced in section 2.5.3. The vehicle torque (T_v) is calculated at the wheel, thus, the motor torque must be multiplied by the transmission ratio (γ), accounting for the gearbox efficiency.

$$P_v \leq k_A k_R^2 \bar{P}_{\max} \eta_{gb} \quad 7.11$$

$$T_v = \frac{P_v}{v} \leq k_A k_R^2 \bar{T}_{\max} \eta_{gb} \gamma \quad 7.12$$

Then a set of performance constraints is imposed via equations 7.13 - 7.15, which impose a maximum vehicle mass, a minimum riding range (R), and a minimum top speed ($v_{\max}$). The performance constraint allows us to avoid solutions that are not implementable (like too high vehicle mass), trivial solutions (null or minimum size battery), and build a motorcycle that can be competitive among the others (top speed).

$$m \leq m_{\max} \quad 7.13$$

$$\frac{C_b}{E_b} D \geq R \quad 7.14$$

$$\sqrt[3]{\frac{\bar{P}_{\max} k_A k_R^2}{\frac{1}{2} \rho_{\text{air}} C_d A}} \geq v_{\max} \quad 7.15$$

Finally, the cost function (J) is expressed as the sum of the specific energy consumption, the inverse of the riding range, and the acceleration time to reach a final velocity of 100 km/h, starting at rest. The calculation of the acceleration time was based on the assumption that the motor operates consistently under constant torque. This assumption holds when the motor's base speed is sufficiently high, ensuring that the vehicle's ultimate velocity falls within the constant torque range. With a motor possessing a high power-to-weight ratio, as commonly found in high-performance motorcycles, and relatively low final speeds, this assumption is valid. A more detailed optimization will be provided in section 7.2.3, accounting also for tire adherence limits and motor losses.

$$t_{\text{acc}} = \int_0^T \frac{m}{F_v} dv = \int_0^T \frac{m}{\frac{k_A k_R^2 \bar{T}_{\max} \gamma \eta_{gb}}{r_w}} dv = \frac{m v_f r_w}{k_A k_R^2 \bar{T}_{\max} \gamma \eta_{gb}} \quad 7.16$$

$$J = \underbrace{\frac{E_b}{D}}_{\text{specific energy consumption}} + \underbrace{\frac{E_b}{C_b D}}_{\text{inverse of riding range}} + \underbrace{\frac{m v_f r_w}{k_A k_R^2 \bar{T}_{\max} \gamma \eta_{gb}}}_{\text{acceleration time}} \quad 7.17$$

Problem 1 (Powertrain Design). *The optimal powertrain designs, which minimize energy consumption, maximize the riding range, and minimize acceleration time, are the solution to the joint design optimization problem*

$$\begin{aligned} & \min_{k_A, k_R, C_b, \gamma} J \\ & \text{s.t. Powertrain Constraints 7.4-7.10} \\ & \text{Performance Constraints 7.13-7.15} \end{aligned}$$

The optimal solutions can be computed via a standard algorithm for the Pareto frontier or an off-the-shelf optimization solver. Results are shown in the figure 7.12, for a minimum range of 80 km, a maximum mass of 310 kg, a minimum top speed of 250 km/h, a specific energy density of 160 Wh/kg, a motor mass of 45 kg, a maximum power of 100 kW, and a maximum torque of 66 Nm. The driving cycle used for the optimization was synthesized as explained in section 5.4, and the vehicle parameters were described in section 4.4.

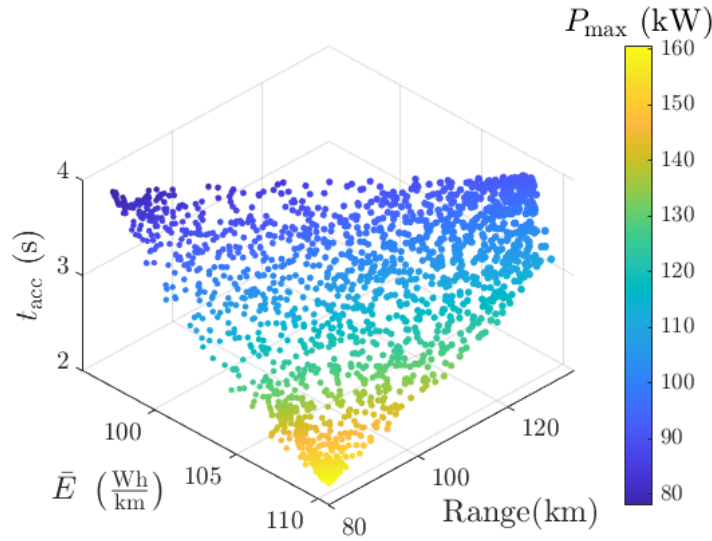


Figure 7.12: Pareto front for three cost functions, the specific energy consumption ($\bar{E}$), the acceleration time (t_{acc}), and the riding range. The dot color indicates the maximum power in kW, while the dot size indicates the battery capacity.

The optimal solutions are plotted in Figure 7.13, for eight parameters, in order: the riding range (R), the vehicle mass (m_v), the battery capacity (C_b), the specific energy consumption ($\bar{E}$), the maximum power (P_{max}), the top speed (v_{max}), the acceleration time from 0 to 100 km/h (t_{acc}), and the transmission ratio (γ). In this latter figure, the solutions were divided linearly into four classes based on the minimum and maximum vehicle mass results.

The transmission ratio was practically the same (12) for all the optimal solutions, the low differences are given due to the optimization tolerance. This latter ratio is the maximum allowed in the optimization, and this fact can be explained by Equation 7.16. Keeping all the other decision variables constant, results in a minimum acceleration time by maximizing the gear ratio, without any consequence on consumption or riding range. A more detailed model might implement the gearbox mass as a function of the transmission ratio, and also the gearbox efficiency might be expressed as a function of the gear ratio. An example is expressed as follows:

$$\eta_{gb} = \begin{cases} 1 & \text{if } \gamma = 1 \\ \frac{\gamma}{\tau_{stage}} \eta_{stage} & \text{if } \gamma > 1 \end{cases}, \quad 7.18$$

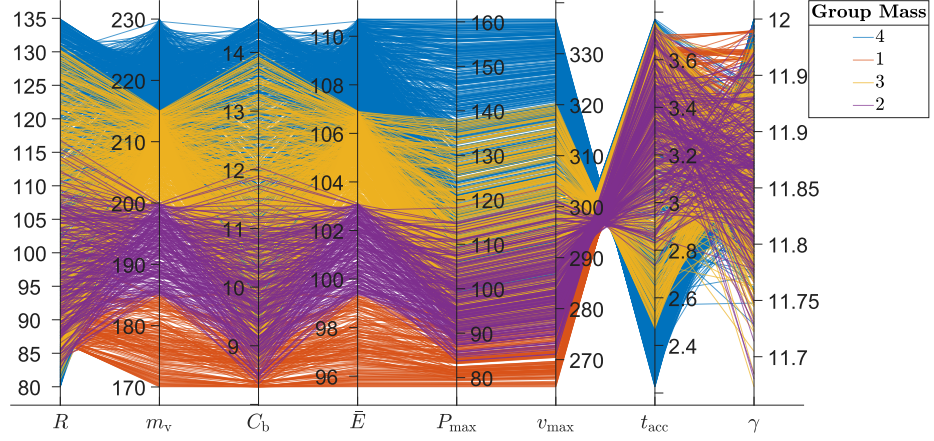


Figure 7.13: Optimal solution parallel plot for seven coordinates: the riding range (R) in km, the vehicle mass (m_v) in kg, the battery capacity (C_b) in kWh, the specific energy consumption ($\bar{E}$) in Wh/km, the maximum power ($P_{\max}$) in kW, the top speed ($v_{\max}$) in km/h, the acceleration time (t_{acc}) in seconds, and the gear ratio (γ).

The gearbox efficiency is expressed as a function of the single-stage efficiency (η_{stage}) and the number of stages, which is the argument of the exponent. This latter formula must be proved, and here it is reported as just an example. The transmission ratio does not influence the maximum power, and because the limit to the top speed is given by the power needed for the traction, a solution with high power also results in a solution with high top speed, as is shown in the figure 7.13. Substituting equations 7.4 into equations 7.16 leads to the conclusion that the higher the power, the lower the acceleration time.

$$t_{\text{acc}} = \frac{\left(m_r + m_0 + k_A k_R^2 m_m + \frac{C_b}{\rho_b}\right) v_f r_w}{k_A k_R^2 \bar{T}_{\max} \gamma \eta_{\text{gb}}} = \frac{\left(m_r + \frac{C_b}{\rho_b}\right) v_f r_w}{k_A k_R^2 \bar{T}_{\max} \gamma \eta_{\text{gb}}} + \frac{m_m v_f r_w}{\bar{T}_{\max} \gamma \eta_{\text{gb}}} \quad 7.19$$

The second term on the right remains constant regardless of motor size, whereas the first term approaches zero as motor size increases. Consequently, enlarging the motor size results in greater top speed and reduced acceleration time. Conversely, integrating Equation 7.4 and Equation 7.5 into Equation 7.8 leads to increased consumption. Hence, achieving minimal acceleration time increases consumption and decreases range due to the vehicle's mass constraints. Increasing battery capacity will similarly raise consumption; however, it will also extend the range. Looking at the first two right terms of the cost function, in equations 7.17, it can be conducted with the example in section 7.2.1, with the battery capacity as the single decision variable. Substituting Equation 7.4 and Equation 7.8 in the first two terms of the cost function in Equation 7.17, and neglecting the third one, results in the following:

$$J = \frac{\sum_i \left(c_1 + c_2 \frac{C_b}{\rho_b}\right)}{D} + \frac{\sum_i \left(c + c_{\text{rr}} \frac{C_b}{\rho_b}\right)}{C_b D} = \frac{\sum_i \left(c_1 + c_2 \frac{C_b}{\rho_b}\right)}{D} + \frac{\sum_i \left(\frac{c_3}{C_b} + c_4\right)}{D} \quad 7.20$$

where c_1 , c_2 , c_3 , and c_4 are constant terms that account for the other parameters, and the integral was replaced with the sum. Thus, to minimize the first term, the battery capacity must be the minimum possible, and to minimize the second term should be the maximum possible, resulting in a cost function conflict. The Pareto frontier plot for the first two objective functions is shown in Figure 7.14, together with the iso-battery capacity line and the iso-mass vehicle line.

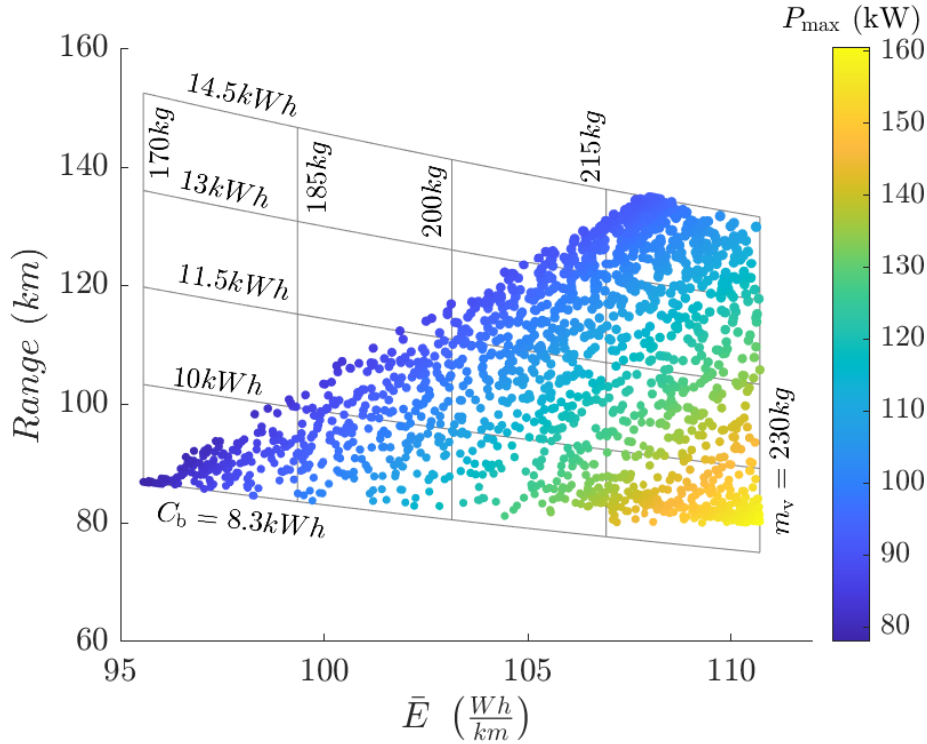


Figure 7.14: Pareto front for the specific consumption-riding range plane. In grey are also plotted the iso-battery capacity in kWh, and the iso-vehicle mass in kg.

The effects on the three cost functions of the decision variables are reported in the Table 7.2. The specified parameters are incremented starting from a reference value, while maintaining all other variables unchanged. The only method to extend the travel range is to enhance the battery capacity. The gear ratio influences only the acceleration time and does not affect the other parameters. Scaling the motor both axially and radially leads to higher consumption, lower range, higher maximum power, higher speed, and higher mass.

Table 7.2: Effect of the variables increment on the specific energy, the riding range, the acceleration time, the maximum power, the top speed, and the mass vehicle.

Parameter increased	$\bar{E}$	Range	t_{acc}	P_{max}	v_{max}	m_v
Gear ratio (γ)	-	-	$\uparrow$	-	-	-
Battery capacity (C_b)	$\uparrow$	$\uparrow$	$\downarrow$	-	-	$\uparrow$
Axial motor scaling (k_A)	$\uparrow$	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$
Radial motor scaling (k_R)	$\uparrow$	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$

To summarize, a framework has been established for optimizing vehicle powertrains, focusing on balancing power, powertrain limits, and performance constraints to achieve a competitive motorcycle design. The essence of the powertrain problem involves modeling all the design aspects as a function of the decision variables. Optimization objectives included minimizing energy consumption, maximizing riding range, and minimizing the acceleration time, but other cost functions could be defined. The investigation highlights the trade-offs inherent in powertrain design, such as increased consumption with higher power outputs and the conflicting requirements of minimizing battery size versus maximizing range. Enhancing battery capacity is a direct method to extend range. At the same time, the transmission ratio mainly affects acceleration time without impacting other parameters, suggesting that a more

sophisticated model should be introduced. The optimization accommodates performance constraints to be competitive among the other vehicles, but other performances could be added depending on the specific motorcycle designer's needs.

7.2.3 Case study: Two-wheel-driven Superbike

This section presents the powertrain design framework, summarized in Figure 7.15, to optimize the gear ratio, rear motor size, battery size, and force distribution between the front and rear motors of an electric superbike. To this end, the energy consumption minimization problem is addressed while accounting for adherence limits and performance constraints. A two-wheel-driven electric motorcycle was considered for the possibility of recovering energy without exceeding the tire adherence limits.

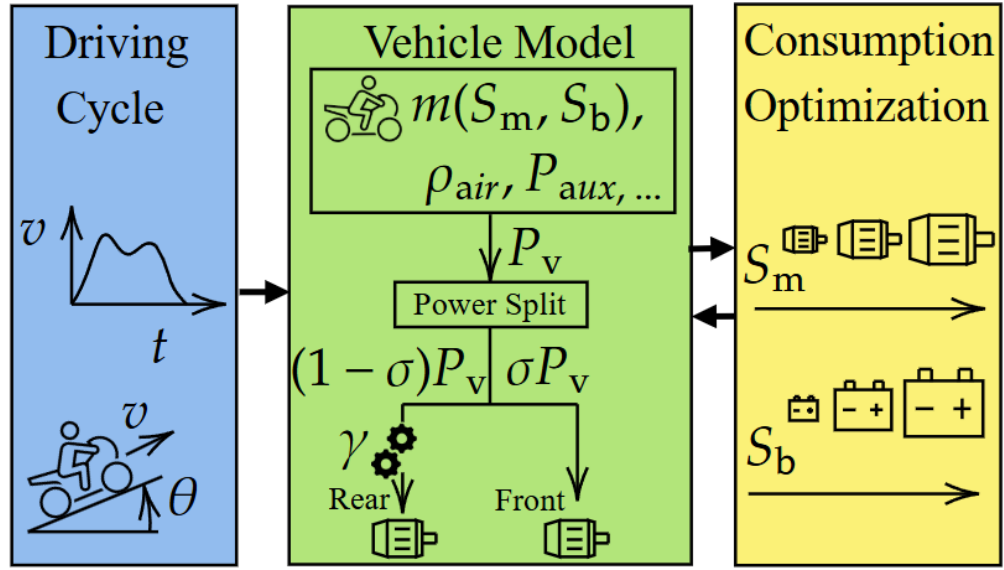


Figure 7.15: Schematic representation of our powertrain design framework. The driving cycle provides the vehicle kinematics for the vehicle operations. The power required and the force distribution are jointly optimized with the gear ratio, motor, and battery sizing, minimizing the energy consumption.

The force required at the wheel is based on the standard and custom driving cycle built-in section 5.4, which provides the vehicle longitudinal speed v , acceleration a , and road inclination θ . The kinematics of the vehicle were linked to its dynamics through a single degree of freedom model, ignoring tire slip and suspension dynamics. Moreover, the power necessary for the vehicle to adhere to the driving cycle is dependent on its mass, which itself is affected by the sizing of the components. Under these hypotheses, the power required at the wheels can be written as:

$$P_v = mv(c_{rr} \cos(\theta) + g \sin(\theta) + a) + \frac{1}{2} \rho C_d A_f v^3 \quad 7.21$$

where m is the overall mass, g is the gravitational acceleration constant, c_{rr} is the tire rolling resistance coefficient, ρ is the air density, C_d is the longitudinal aerodynamic drag coefficient, and A_f is the front cross-section area. The total mass is influenced by the dimensions of the rear motor and battery, along with fixed factors like the rider's mass m_r and the glider's mass m_0 (including the front motor).

$$m = m_0 + m_r + \bar{m}_b \cdot S_b + \bar{m}_m^r \cdot S_m^r, \quad 7.22$$

where $\bar{m}_b$ and $\bar{m}_m^r$ are the reference battery and rear motor mass, respectively. The scaling factors for the battery S_b and for the rear motor S_m^r linearly adjust the size of the components to satisfy the power demand. High-performance motorcycle riding is characterized by high load transfers from one wheel to the other. Hence, keeping the same braking effort on a wheel independently of the load transfer might result in locking, with serious consequences on safety. For this reason, the power split between the front and rear wheels σ might be based on the strategy that maximizes tire adherence σ^a to ensure vehicle stability [166], and is calculated by Equation 4.121 by changing the sign to F_D and neglecting the aerodynamic effects, resulting as follows:

$$\sigma^a = \frac{b}{w_b} - \frac{h}{w_b} \left(\frac{X_f + X_r}{m g \cos(\theta)} - c_{rr} \right), \quad 7.23$$

where X_f and X_r are the longitudinal front and rear force respectively, b is the longitudinal distance between the rear wheel contact point to the vehicle center of mass, w_b is the distance between the front and rear axles (wheelbase), and h is the height of the vehicle center of mass. Since this strategy is not necessarily the optimal choice when minimizing energy consumption, to ensure the motor is operated in the most efficient region we jointly optimize the gear ratio γ and σ , distributing the longitudinal power required P_v between front P_v^f and rear P_v^r as

$$P_v^f = \sigma P_v, \quad 7.24$$

$$P_v^r = (1 - \sigma) P_v, \quad 7.25$$

$$\sigma \geq 0 \quad 7.26$$

$$\sigma \leq 1 \quad 7.27$$

where the superscripts f and r indicate the front and rear wheels, respectively. Summing Equation 7.24 to Equation 7.25 reduces to Equation 7.21. However, for safety reasons to avoid the locking of the front wheel a constraint on the adherence was imposed.

$$\sigma \leq \sigma^a. \quad 7.28$$

The net force acting on each wheel is further divided among the force supplied by the motors F_m^f and F_m^r , the dissipative brakes F_{brk}^f and F_{brk}^r , and the tractive force F_{tr}^f . The tractive term accounts for the force transfer from the front wheel to the other in the case of motor saturation, redistributing the missing torque on the other wheel.

$$F_v^f = \sigma \frac{P_v}{v} = F_m^f + F_{brk}^f + F_{tr}^f, \quad 7.29$$

$$F_v^r = (1 - \sigma) \frac{P_v}{v} + F_{tr}^f = F_m^r + F_{brk}^r. \quad 7.30$$

The tractive force is needed due to the lower power capacity of the front motor; in fact, summing Equation 7.29 to Equation 7.30, the term is on both sides of the equality and is simplified. This latter force is needed only on traction because during braking, in case of motor saturation, the mechanical braking can supply the requested force. While the front wheel locking during braking is prevented by Equation 7.28, the locking on the rear wheel is prevented by imposing a rear tire threshold $\mu_{brk,peak}^r$ constraint on the rear wheel adherence μ^r

$$\mu^r = \frac{X_r}{\frac{m \cdot g \cdot \cos(\theta)}{w_b} (w_b - b - h \cdot c_r) + \frac{h}{w_b} (X_f + X_r)}, \quad 7.31$$

$$\mu^r \geq \mu_{\text{brk,peak}}^r, \quad 7.32$$

so that the rear tire adherence is greater than or equal (braking adherence has negative values) to the maximum adherence allowed to prevent the wheel locking. Furthermore, the required braking force is applied serially: first, by regenerative braking, then by mechanical braking

Finally, the mutual exclusion between the motor tractive and braking forces was guaranteed by introducing constraints on the sign of the repartitioned forces, ensuring coherence between the tractive and braking forces

$$F_m^f F_m^r \geq 0, \quad 7.33$$

$$F_{\text{brk}}^f \leq 0, \quad 7.34$$

$$F_{\text{brk}}^r \leq 0, \quad 7.35$$

$$F_{\text{tr}}^f \geq 0, \quad 7.36$$

$$F_m^f F_{\text{brk}}^f \geq 0, \quad 7.37$$

$$F_m^r F_{\text{brk}}^r \geq 0. \quad 7.38$$

Equation 7.33 imposes that both motors must provide forces of the same sign or at least one could be null. So the motors both operate in traction mode, braking mode, or one might be idling. Equation 7.34 together with Equation 7.37 imposes the coherence between the front braking force supplied via mechanical braking and the motor force, so the mechanical braking can be supplied only if the front motor is braking. The analogous for the rear mechanical braking and rear motor is imposed by Equation 7.35 and Equation 7.38. Equation 7.36 sets the constraint on the tractive force, which must be positive or null, because, as suggested by the name itself can be needed only during traction for repartitioning the force from the front wheel to the rear wheel in case of front motor power or torque saturation. The front in-wheel motor, characterized in the work of [166], is directly coupled to the wheel without any reduction. The power required by the front motor P_m^f can be derived from the force at the wheel and the vehicle speed. Conversely, the rear frame-mounted motor is connected to the wheel via a single-speed fixed-gear transmission. For this reason, we also need to account for the driveline efficiency η_{gb} when estimating the power required P_m^r

$$P_m^f = F_m^f \cdot v \quad 7.39$$

$$P_m^r = \begin{cases} \frac{1}{\eta_{\text{gb}}} F_m^r \cdot v & \text{if } F_m^r \geq 0 \\ F_m^r \cdot v \cdot \eta_{\text{gb}} & \text{if } F_m^r < 0 \end{cases}, \quad 7.40$$

Equation 7.40 can be relaxed to a set of linear inequalities, without changing the optimal solution [202], as follows:

$$P_m^r \geq \frac{1}{\eta_{\text{gb}}} F_m^r \cdot v \quad 7.41$$

$$P_m^r \geq F_m^r \cdot v \cdot \eta_{\text{gb}}$$

The first inequality holds positive power because it is greater than the second inequality, and vice versa, the second inequality holds negative powers. Briefly, the reason is that in traction, the minimum possible power must be provided, and in braking, the minimum (negative value) possible power would be recovered by the motors. The motor speed ω_m^f and ω_m^r can be computed directly by the vehicle speed, assuming null tire slip, as

$$\omega_m^f = \frac{v}{r_w^f}, \quad 7.42$$

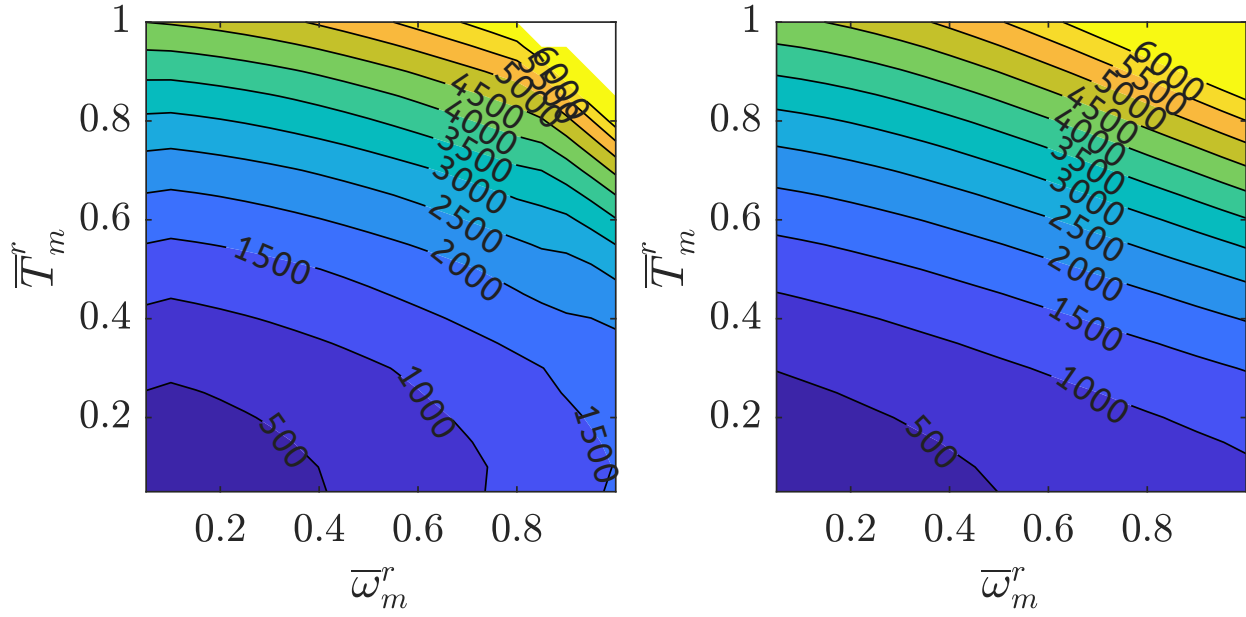


Figure 7.16: Comparison between the normalized data (left) of the rear electric motor power losses (in W) and our model (right). The R^2 was equal to 0.99, with an NMRSE of 2.8%

$$\omega_m^r = \frac{v \cdot \gamma}{r_w^r}. \quad 7.43$$

where r_w^f and r_w^r are the wheels radii and γ the gear ratio of the transmission. This latter ratio was constrained to its uppermost value when the top vehicle speed $v_{\max}$ matches the maximum rear motor speed $\omega_{m,\max}^r$

$$\gamma \leq \frac{\omega_{m,\max}^r \cdot r_w^r}{v_{\max}} \quad 7.44$$

In the framework, the front motor is of constant size, while the rear motor is linearly scaled along its axial dimension via the scaling laws for synchronous machine [272], varying its power $P_{m,\max}^r$ and torque $T_{m,\max}^r$ concerning the reference motor

$$S_m^r = \frac{P_{m,\max}^r}{\bar{P}_{m,\max}^r} = \frac{T_{m,\max}^r}{\bar{T}_{m,\max}^r}, \quad 7.45$$

where S_m^r is the rear electric machine scaling factor, $\bar{P}_{m,\max}^r$ and $\bar{T}_{m,\max}^r$ are the reference motor maximum power and torque, respectively. While for the front motor losses P_{loss}^f we used the same approach of [166], the rear motor map provided directly by Ducati, and its power losses are estimated using a polynomial fit of the speed and motor torque (Fig. 7.16), described in [184], and scaling the iron, mechanical, and copper losses of the reference motor, $\bar{P}_{\text{Fe}}^r$, $\bar{P}_{\text{Mech}}^r$, and $\bar{P}_{\text{Cu}}^r$ as

$$P_{\text{loss}}^f = a_l \omega_m^f + b_l (\omega_m^f)^2 + c_l (\omega_m^f)^3 + d_l (T_m^f)^2 \quad 7.46$$

$$P_{\text{Fe}}^r = S_m \cdot a_{\text{Fe}} \cdot \omega_m^r \quad 7.47$$

$$P_{\text{Mech}}^r = S_m (a_{\text{Mech}} + b_{\text{Mech}} \cdot \omega_m^r + c_{\text{Mech}} (\omega_m^r)^2 + d_{\text{Mech}} (\omega_m^r)^3) \quad 7.48$$

$$P_{\text{Cu}}^r = \left(\frac{S_m \cdot l_{\text{co}}}{l_{\text{co}} + l_{\text{ew}}} + \frac{l_{\text{ew}}}{l_{\text{co}} + l_{\text{ew}}} \right) (a_{\text{Cu}} + b_{\text{Cu}} (\omega_m^r)^2) \left(\frac{P_m^r}{\omega_m^r S_m} \right)^2 \quad 7.49$$

where a_l , b_l , c_l , d_l , a_{Fe} , a_{Mech} , b_{Mech} , c_{Mech} , d_{Mech} , a_{Cu} , and b_{Cu} are identified loss coefficients, l_{co} is the stack length, and l_{ew} is the end winding length. Each motor is also bound to not exceed its operational limits

$$P_m^f \leq P_{m,max}^f, \quad 7.50$$

$$P_m^r \leq \bar{P}_{m,max}^r S_m, \quad 7.51$$

$$F_m^f r_w^f \leq T_{m,max}^f, \quad 7.52$$

$$\frac{P_m^r}{\omega_m^r} \leq \bar{T}_{m,max}^r S_m, \quad 7.53$$

where $\bar{P}_{m,max}^r$ is the maximum reference rear motor power, $T_{m,max}^f$ the maximum front motor torque, and $\bar{T}_{m,max}^r$ the maximum rear reference motor torque. The Equation 7.53 uses the rear power over the speed to define the rear torque to consider the driveline efficiency. The overall electric motors power P_{ac} can be written as

$$P_{ac} = P_m^f + P_{loss}^f + P_m^r + P_{Cu}^r + P_{Fe}^r + P_{Mech}^r \quad 7.54$$

The battery power P_b is equal to the sum of overall motor input power P_{ac} and the auxiliaries consumption P_{aux} , considering the inverter and battery efficiency η_{inv} and η_b

$$P_b = \begin{cases} \left(\frac{P_{ac}}{\eta_{inv}} + P_{aux} \right) (\eta_b)^{-1} & \text{if } P_b \geq 0 \\ (\eta_{inv} P_{ac} + P_{aux}) \eta_b & \text{if } P_b < 0 \end{cases}. \quad 7.55$$

Because P_{aux} is always positive in this model, Equation 7.55 can be relaxed to a set of linear inequality constraints as

$$\begin{aligned} P_b &\geq \left(\frac{P_{ac}}{\eta_{inv}} + P_{aux} \right) (\eta_b)^{-1} \\ P_b &\geq (\eta_{inv} P_{ac} + P_{aux}) \eta_b \end{aligned} \quad 7.56$$

The first inequality holds for positive battery power, while the second holds for negative battery power. The power flow causes a change in battery energy E_b following the equation

$$\frac{dE_b}{dt} = -P_b \quad 7.57$$

integrating over time, the battery power is leading to an overall energy consumption E_c computed as

$$E_c = (E_b(0) - E_b(T)),$$

where $E_b(0)$ is the energy at the beginning of the driving cycle and $E_b(T)$ is the energy remaining at its end. To optimize the size of the battery is introducing a battery scaling factor S_b , linking the full battery capacity $E_{b,max}$ to the reference full battery capacity $\bar{E}_{b,max}$, as suggested by the analysis in section 5.2.

$$S_b = \frac{E_{b,max}}{\bar{E}_{b,max}}. \quad 7.58$$

Ultimately, the battery energy is constrained in its operational range by

$$E_b \in \left[\bar{E}_{b,max} \cdot \xi_{min}, \bar{E}_{b,max} \cdot \xi_{max} \right] \cdot S_b, \quad 7.59$$

through the coefficients of minimum and maximum state of charge ξ_{min} and ξ_{max} , for not fully charging or discharging the battery and avoiding or mitigating excessive wear.

The driving cycle provides useful insights on the riding style, but it is not fully representative of all the performance required to rank the design motorcycle among the other vehicles present in the market, for instance, it does not constrain the riding range. For this reason, performance constraints were included on maximum acceleration time, maximum speed, power gradeability, torque gradeability, and riding range. The constraint on the top speed on a flat surface can be found by imposing a balance on the maximum motor power as

$$P_{m,\max}^f + P_{m,\max}^r S_m \eta_{gb} \geq \frac{1}{2} \rho C_d^p A_f^p v_{\max}^3 + m g c_{rr} v_{\max} \quad 7.60$$

where the superscript p indicates a rider sitting prone on the motorcycle, for a 10% air resistance power reduction [50]. From the power balance and equation of motion on the uphill driving with the maximum road grade $\theta_{\max}$ at the minimum speed $v_{\min}$ leads to the constraint to gradeability, neglecting the aerodynamic and tire rolling resistance as follows:

$$P_{m,\max}^f + S_m \bar{P}_{m,\max}^r \eta_{gb} \geq m g \sin(\theta_{\max}) v_{\min} \quad 7.61$$

$$\frac{T_{m,\max}^f}{r_w^f} + \frac{S_m \bar{T}_{m,\max}^r \gamma \eta_{gb}}{r_w^r} \geq m g \sin(\theta_{\max}) \quad 7.62$$

The minimum riding range D_r constraint can be expressed as a function of the driving cycle energy consumption and distance D_c as in Equation 7.63.

$$E_b(0) - E_b(T) \leq S_b (\xi_{\max} - \xi_{\min}) \bar{E}_{b,\max} \frac{D_c}{D_r}, \quad 7.63$$

The acceleration time is the time to reach a final speed v_f from the vehicle's rest. To define the acceleration time, there could be four different combinations of motor operating, assuming a coherence between them (i.e., both traction). The first combination is when the vehicle starts from rest, both motor works in a constant torque region. The other two combinations are when the front motor works in the power constant region and the rear motor is still working in the constant torque region, and vice versa. Finally, the last situation is when both motor works in the power constant zone. Due to the possibility of matching the rear-mounted motor with the vehicle speed through the gearbox, a high power-to-weight ratio can be implemented. Thus the rear motor base is higher than the front motor. Assuming a final speed that is lower than the rear base speed ω_r^r , the rear motor is always working in the constant torque region. The front motor starts operating in the constant torque region and then in the constant power region due to the lower base speed. From the equation of motion, and neglecting the rotary inertia, the acceleration time can be calculated by integrating over time as

$$\int_0^{t_{\text{acc}}} 1 dt = \int_0^{v_f} \frac{m}{F} dv \quad 7.64$$

The force can be expressed as a function of the maximum motor torques and power, by splitting the integral interval as follows:

$$t_{\text{acc}} = \int_0^{\omega_r^f r_w^f} \frac{m}{\frac{T_{m,\max}^f}{r_w^f} + \frac{S_m \gamma \bar{T}_{m,\max}^r \eta_{gb}}{r_w^r}} dv + \int_{\omega_r^f r_w^f}^{v_f} \frac{m}{\frac{P_{m,\max}^f}{v} + \frac{S_m \gamma \bar{T}_{m,\max}^r \eta_{gb}}{r_w^f}} dv \quad 7.65$$

where ω_r^f is the front motor rate or base speed. Manipulating the previous equation led to

the final expression as follows:

$$t_a \geq \frac{m \cdot \omega_r^f \cdot r_w^f}{\frac{T_{m,\max}^f}{r_w^f} + \frac{S_m \cdot \gamma \cdot \bar{T}_{m,\max}^r \cdot \eta_{gb}}{r_w^r}} + \frac{m \cdot r_w^r}{S_m \cdot \gamma \cdot \bar{T}_{m,\max}^r \cdot \eta_{gb}} \left[(v_f + \right. \\ \left. - \omega_r^f \cdot r_w^f) - \frac{P_{m,\max}^f \cdot r_w^r}{\gamma \cdot S_m \cdot \bar{T}_{m,\max}^r \cdot \eta_{gb}} \log \left(\frac{P_{m,\max}^f + \frac{v_f r_w^r}{S_m \cdot \gamma \cdot \bar{T}_{m,\max}^r \cdot \eta_{gb}}}{P_{m,\max}^f + \frac{\omega_r^f \cdot r_w^r}{S_m \cdot \gamma \cdot \bar{T}_{m,\max}^r \cdot \eta_{gb}}} \right) \right], \quad 7.66$$

The vehicle must accelerate in time equal to or lower than a threshold value. Like for Equation 7.16 in section 7.2.2, the higher the value of γ and the lower the acceleration time, keeping the other parameters constant. Finally, the cost function is formulated for the design optimization as

$$J = E_c + w \sum_{t=1}^T F_{tr}^f, \quad 7.67$$

composed of the energy consumption over the driving cycle E_c and tractive terms responsible for the force transfer in the case of motor saturation, weighted by the parameter w . In fact, including the last term is essential to enforce the force repartition between the motors depending on the bias strategy. Otherwise, in the case of different power repartition strategies, if the rear motor is more efficient than the front will result in zero front force and the torque will be provided by only the rear wheel due to the presence of the tractive force term.

Problem 2 (Powertrain Design). *The optimal powertrain design and propulsion blending strategy to minimize energy consumption is the solution to the joint design optimization problem*

$$\begin{aligned} & \min_{\gamma, \sigma, S_m, S_b} J \\ & s.t. \text{ Powertrain Constraints, Equations 7.21-7.59} \\ & \text{Performance Constraints, Equations 7.60-7.63, 7.66} \end{aligned}$$

An optimal solution can be found using standard nonlinear programming methods. Here are some assumptions and limitations of the framework: First, the rear electric machine's mass, torque, power, and losses were assumed to scale linearly according to typical axial scaling laws for synchronous permanent magnet motors, while the front motor's size was kept constant due to its impact on lateral dynamics and the limited space in the front wheel. Second, changes in gear ratio were assumed not to significantly impact vehicle mass and driveline efficiency. Additionally, displacements of the center of gravity due to component sizing were neglected, and it was assumed that aerodynamic forces act on the vehicle's center of mass. Despite these assumptions, the propulsive blending optimization remains valid since it relies only on motor losses and not vehicle geometry [166]. Inverter and battery losses were modeled using constant efficiencies. Although more sophisticated models are possible, the problem remains non-convex and can be addressed with generally off-the-shelf solvers.

Finally, the regenerative ratio ζ and the average efficiency η are introduced as measures to understand the benefits of the propulsive blending strategy and its influence on energy consumption. While both indicators can vary from 0 to 100 % (ideal powertrain), ζ indicates how much energy is recuperated during the drive cycle in absolute terms, while η takes into account the energy needed for the vehicle propulsion as well

$$\zeta = \frac{|E_{b,in}|}{E_{b,out}} \cdot 100, \quad 7.68$$

$$\eta = \frac{E_{v,tr} + E_{v,brk}}{E_{b,out} + E_{b,in}} \cdot 100 = \frac{E_{v,tr} + E_{v,brk}}{E_{b,out}(1 - \zeta/100)} \cdot 100, \quad 7.69$$

where $E_{v,tr}$ is the vehicle or mechanical traction energy (positive), $E_{v,brk}$ is the vehicle braking energy (negative), $E_{b,out}$ is the overall energy flowing out of the battery (positive) and $E_{b,in}$ flowing in (negative). The indicators ζ and η link the energy reduction resulting from the joint design to the specific contributions of net lower mechanical energy (numerator) and higher regeneration ratio.

7.2.4 Optimization Results

The problem was discretized with a sampling time of 1 s and the forward Euler method and solved using the nonlinear solver IPOPT [291] after parsing it with CasADi [15]. The results suggest that the joint optimization of sizing and force distribution can significantly reduce the mass and average energy consumption over the driving cycle $\bar{E}_c$, allowing for smaller and cheaper motors and batteries. The framework was applied, using standard cycles (UDSS, WMTC) and custom cycles (Sport), with two propulsive biases: the adherence-based (σ_a) and the optimal (σ^*). Figure 7.17 shows the vehicle speed, the power repartition, and the propulsive bias in a 20-second window of the sport cycle. The driving range was set to 100 km, the acceleration time to 3.5 s, the maximum speed to 250 km/h, and the road angle (θ_{max}) to 14 (slope of 25%) at a minimum speed of 15 km/h and the battery energy operation limit, via the minimum and maximum SoC parameters (ξ_{min} , ξ_{max}) was set between 10% (not completely discharged) to 90% (not completely charged). The auxiliary power was equal to 100 W because a motorcycle does not need high auxiliary power like the A/C air system. Considering a dry and good road, the adherence limit (μ_{brk}^f) was equal to 0.8. The mass vehicles, battery capacity, rear motor power, and specific energy consumption results are reported in Table 7.3. The vehicle and performance parameters are reported in Table 7.5. The transmission ratio (γ) was the same for all the cases, independently of the cycle and the propulsive bias. This latter ratio was equal to the maximum allowed by equations 7.44; indeed, a higher gear ratio value means a higher wheel torque, and a smaller motor fixed the acceleration time from Equation 7.65. On the other hand, the motor speed increased with the transmission ratio, so all the losses related to it increased, while the losses related to the torque decreased. All the vehicles obtained the maximum acceleration time and the minimum driving range because higher values of these latter performances lead to mass and consumption increment, due to a bigger motor or battery, as found in section 7.2.2 and summarized in table 7.2.

The adherence propulsive bias logic is the best solution for a safe ride, but as shown from the results is not the solution that minimizes consumption. Indeed, this latter bias had the highest consumption for all the driving cycles. The lowest difference in consumption between the optimal bias (σ^*) and the ideal adherence bias (σ^a) was 4.68% for the WMTC part 3, while the highest was 22.36% for the Sport cycle. The vehicle mass ranged from the lowest value of 159.44 kg (σ^* , UDSS) to the highest 224.71 kg (σ^a , Sport), while the rear motors maximum power ranged from 75.56 kW (σ^* , UDSS) to 98.69 kW (σ^a , Sport). The regenerative ratio (ζ) was defined as the ratio between the battery input power and the input and output power sum in absolute terms. This latter ratio can increase because more energy is recovered during braking, or less energy is delivered, or both. The regenerative ratio ranged from the lowest value of 1.47% to the highest 24.39%, which was similar to the regenerative ratio investigated in a previous analysis [213]. The UDSS had the lowest specific energy consumption (34.07 Wh/km) with the optimal bias, while the highest was the Sport (103.45 Wh/km) with the adherence bias. The highest battery capacity was 12.93 kWh (Sport, ideal), more than twice the lowest value of 4.26 kWh (σ^* , UDSS). The maximum

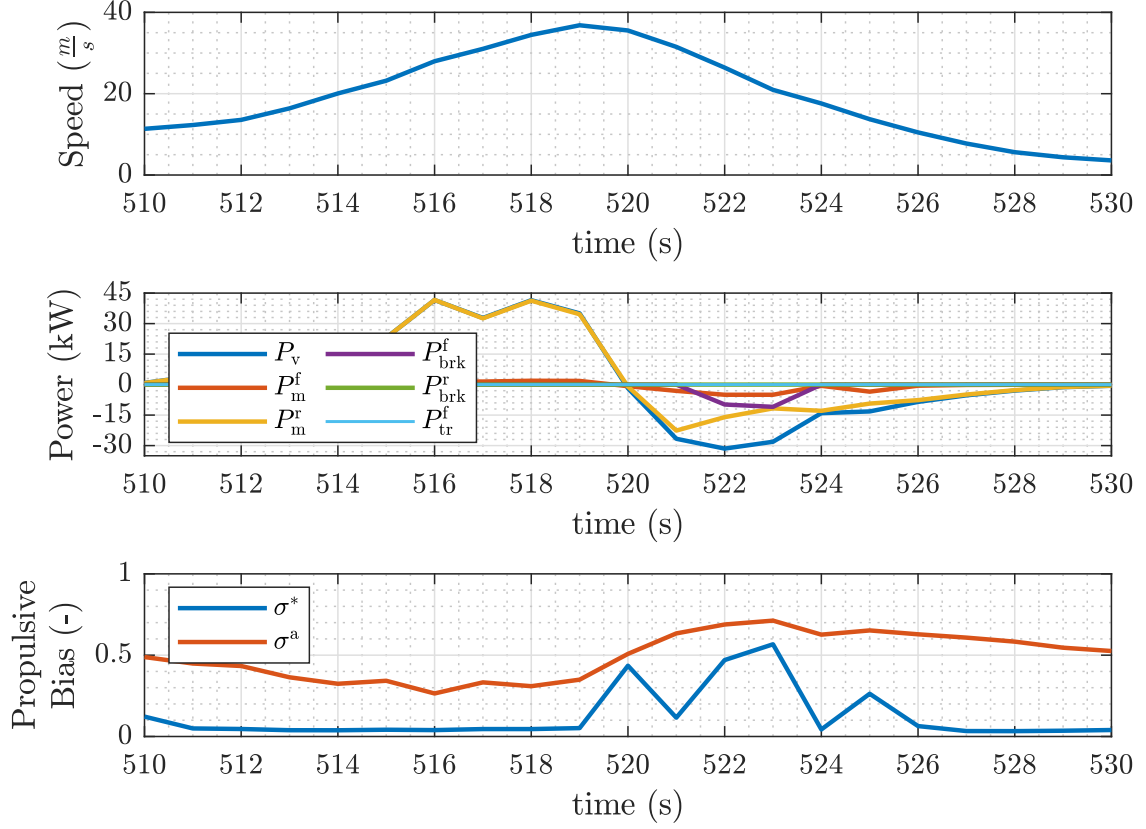


Figure 7.17: A 20 seconds window of the Sport drive cycle, showing the speed profile followed by the vehicle at the top, the power repartition with the optimal propulsive strategy σ^* in the middle, and the comparison between the two different strategies σ^a and σ^* at the bottom.

power changed less than 4% for all the driving cycles, except the Sport (-7.82%). This latter fact can be explained by the lower influence on the top speed due to the mass increment. The lower σ^a logic efficiency meant an increment of the battery size to guarantee the minimum range. An increment of the mass also led to an increment in the maximum power required for the top speed in Equation 7.60. The main part of the power at the top speed is due to the aerodynamic resistance, and so an increment in vehicle mass does not significantly change the maximum required power. Notably, the variation in results between the two propulsion biases is minor in driving cycles where braking power is less crucial, such as in WMTC part 3, compared to a *dynamic* cycle like the Sport. Specifically, during acceleration and traction, the rear motor is predominantly utilized due to load transfer to the rear wheel according to adherence logic. Conversely, during braking, the front wheel bears more force, but the low front motor power is not enough for the recovery of all the braking power, resulting in greater energy dissipation due to the mechanical braking. Therefore, in driving cycles like WMTC part 3, where traction activities are preponderant, the adherence bias is less penalized compared to the optimal bias. However, the adherence logic had more sensible consumption than the optimal bias for driving cycles with smaller dynamics and lower power, like the WMTC part 1 and UDDS. Thus, the rear motor has a higher efficiency than the front motor, especially at low powers and speeds. Looking at the regenerative ratio for these two latter cycles, there was a significant variation, meaning that a higher portion of the power was dissipated.

Table 7.3: Output of the powertrain design optimization for different driving cycles. We compare the adherence-driven propulsive strategy σ^a with the optimal found by our framework σ^* .

Cycle	σ^a				σ^*			
	m_v (kg)	$E_{b,max}$ (kW h)	$P_{m,max}^r$ (kW)	$\bar{E}_c$ ($\frac{Wh}{km}$)	m_v (kg)	$E_{b,max}$ (kW h)	$P_{m,max}^r$ (kW)	$\bar{E}_c$ ($\frac{Wh}{km}$)
WMTC part 1	167.95	5.39	78.57	43.12	159.63 (-4.95%)	4.29 (-20.50%)	75.62 (-3.75%)	34.28 (-20.50%)
WMTC part 2	175.12	6.34	81.11	50.75	170.64 (-2.56%)	5.75 (-9.4%)	79.52 (-1.96%)	45.97 (-9.4%)
WMTC part 3	204.76	10.28	91.62	82.23	201.13 (-1.77%)	9.80 (-4.68%)	90.33 (-1.40%)	78.38 (-4.68%)
WMTC	190.67	8.41	86.64	67.30	185.85 (-2.54%)	7.77 (-7.65%)	84.92 (-1.98%)	62.15 (-7.65%)
UDDS	166.00	5.13	77.88	41.04	159.44 (-3.94%)	4.26 (-16.96%)	75.56 (-2.98%)	34.07 (-16.96%)
Sport	224.71	12.93	98.69	103.45	202.95 (-9.69%)	10.04 (-22.36%)	90.98 (-7.82%)	80.31 (-22.36%)

The table 7.4 summarizes the regenerative ratio (ζ) and average efficiency (η) for different driving cycles under two distinct strategies, σ^a and σ^* . The WMTC 3 has the lowest regenerative ratio for both strategies, but the highest average efficiency. In contrast, the Sport cycle demonstrates the highest regenerative ratio and a moderate to high average efficiency. Overall, strategy σ^* always results in a higher regenerative ratio and efficiency compared to σ^a across all cycles. The UDDS and the WMTC 1 have an efficiency lower than the Sport cycles, likely due to the high-performance constraint. Indeed, to reach a high top speed and lower acceleration time requires powerful motors, leading to an over-dimensioned motor and less efficient for riding operation. The average efficiency allows us to compare results from different cycles for the same vehicle architecture. A rear powerful mounted motor and a front

Table 7.4: Regenerative ratio and average efficiency for the different strategies and driving cycles.

Cycle	σ^a		σ^*	
	ζ (%)	η (%)	ζ (%)	η (%)
WMTC 1	6.28	44.26	11.77	54.4
WMTC 2	6.52	63.62	8.92	69.76
WMTC 3	1.47	74.49	1.85	77.95
WMTC	3.22	68.74	4.61	74.07
UDDS	5.42	49.24	10.23	58.33
Sport	14.60	47.78	24.39	59.64

light motor can achieve high efficiency, more than 70 % for the WMTC part 3 and WMTC. Furthermore, this vehicle architecture also performed well on the WMTC 2, which represents suburban riding. While for urban riding like the WMTC 1 e UDDS, this architecture does not work well as for the other, albeit obtaining an efficiency higher than 50%. For the Sport cycle, the average efficiency is significantly lower compared to the best result, due to the low power of the front motor and the rear tire adherence saturation rear. The rear power loss for the Sport cycle and optimal policy is shown in Figure 7.18.

Some considerations are needed regarding tire adherence, particularly for the Sport cycle.

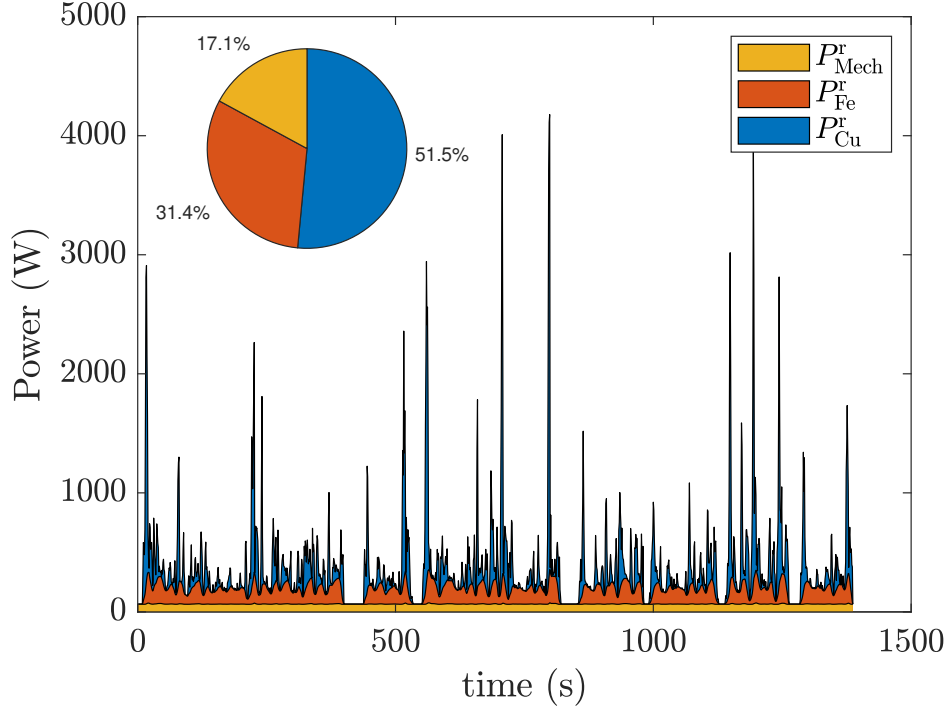


Figure 7.18: Rear motor losses, subdivided by the mechanical P_{Mech}^r (17.1%), core P_{Fe}^r (31.4%), and copper P_{Cu}^r (51.5%), for the Sport cycle with the optimal bias.

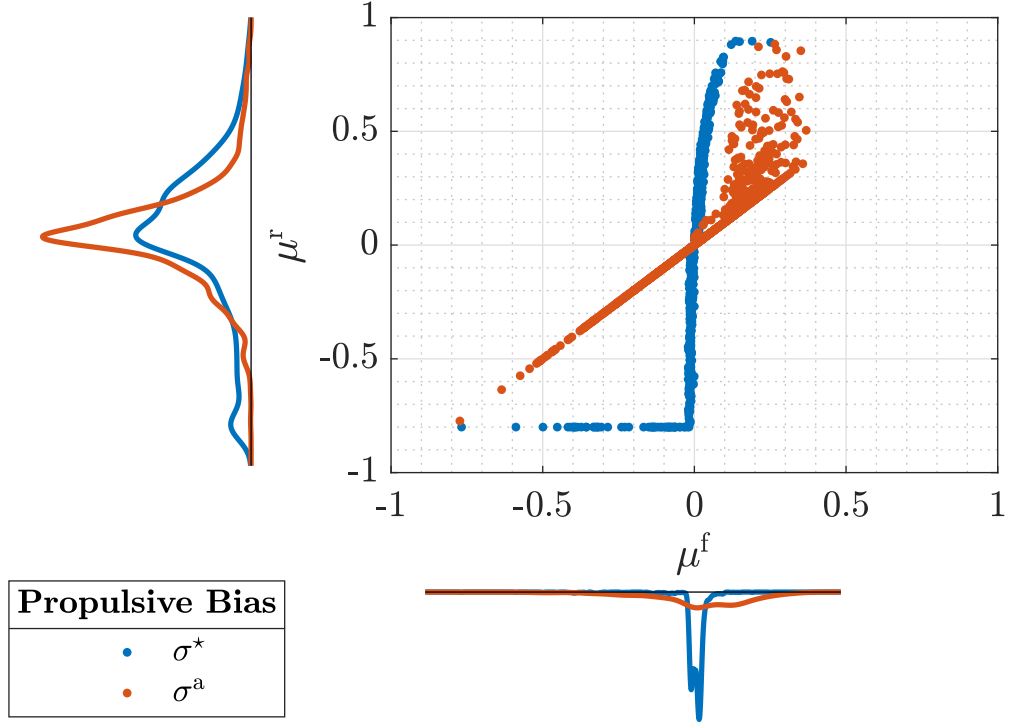


Figure 7.19: Adherence distribution on the front-rear adherence plane for the optimal bias σ^* (blue dots) and the adherence bias σ^a (orange dots). Negative values mean braking operation, and positive values mean tractive operation.

The locking of the front wheel could happen only when both the wheels are locked (i.e., maximum road allowed adherence was exceeded), in the optimal propulsive bias logic, a threshold contained the rear braking force. Since the road's adherence limit is unknown in

advance, rear wheel locking may occur. Although an anti-locking system could intervene to avoid the full lock, it is a potentially unsafe situation that must be avoided. For the standard cycles, the adherence does not reach high values in good road conditions that are far from dangerous situations. The adherence logic can always be followed during braking, as shown in Figure 7.19 due to the possibility of activating the mechanical braking. While during traction due to the lower front power is not always followed. The optimal bias instead tends to privilege the rear motor, reaching the saturation limit imposed on braking (-0.8). In the first quadrant, the front motor is activated sensibly for the high adherence value of the rear wheel.

Table 7.5: Vehicle and Performance Parameters.

Symbol	Value	Unit	Description
m_r	80	kg	Rider mass
m_0	75	kg	Glider mass
r_w^f	0.321	m	Front wheel radius
r_w^r	0.318	m	Rear wheel radius
h	0.573	m	CoG vertical height
b	0.6935	m	CoG longitudinal distance
w_b	1.37	m	Wheelbase
c_r	0.015	-	Tire rolling resistance
$C_d A_f$	0.32	m ²	Drag coefficient
$\mu_{brk,max}$	-0.8	-	Braking rear adherence limit
ρ_{air}	1.25	$\frac{kg}{m^3}$	Air density
g	9.81	$\frac{m}{s^2}$	Gravitational acceleration
η_{gb}	0.96	-	Gearbox efficiency
η_b	0.92	-	Battery efficiency
η_{inv}	0.96	-	Inverter efficiency
P_{aux}	100	W	Auxiliary power
$P_{m,max}^f$	5	kW	Max front motor power
$T_{m,max}^f$	131	N m	Max front motor torque
ξ_{min}	0.1	-	Min battery SoC
ξ_{max}	0.9	-	Max battery SoC
v_{max}	250	$\frac{km}{h}$	Top speed
θ_{max}	25	%	Max road slope climbing
v_{min}	15	$\frac{km}{h}$	Min climbing speed
v_f	100	$\frac{km}{h}$	Final acceleration velocity
t_a	3.5	s	Min acceleration time
D_r	100	km	Min riding range
w	10 ³	-	Cost function weight

The presented framework successfully optimizes the design and operations of a two-wheel-driven electric superbike Powertrain. Specifically, the optimization of the gear ratio, force distribution (propulsion blending strategy), and rear motor and battery size to minimize energy consumption. To this end, the vehicle energy consumption model was devised, including a scalable power loss model for the rear motor based on efficiency maps and accounting for performance constraints and adherence limits. The framework was applied to a case study

that analyzes different driving cycles, comparing the adherence-driven blending strategy with the optimal solution. The joint design of the propulsion strategy and components significantly reduced the vehicles energy consumption compared to the sole optimization of the components with the adherence-driven blending strategy, ranging from 4.68% (WMTC part 3) to 22.36% (Sport). This result highlights the importance of jointly optimizing the powertrain and the force distribution in electric motorcycles and demonstrates the capabilities of our framework.

Finally, this work opens the field for further development, such as developing a cost model, extending the size optimization to the front motor, and including constraints on the vehicles lateral dynamics

8. CONCLUSIONS

The study presented a comprehensive analysis of electric superbike sizing and the corresponding driving cycle definition. The research provided valuable insights into real-world motorcycle dynamics, powertrain losses, regenerative braking strategies, and an optimization framework for an all-electric two-wheel-driven motorcycle. However, several limitations should be considered when interpreting the results.

Using data from the manufacturers, the motorcycle's mass was strongly correlated with the battery capacity, and so was the energy consumption. These latter aspects result in the riding range law, which describes the increment in riding range as a function of the vehicle mass. According to this simple model, the riding range can be extended by increasing the battery until the consumption also rises too much, balancing the increment of battery capacity. Therefore, the increment of battery capacity ought to be a good strategy since the motorcycle has a low mass, as shown by the sensitivity analysis.

Vehicle dynamics, with attention on vehicle energy consumption, was described. In particular, the investigation on losses due to the longitudinal and lateral slip power losses. An analytical model to describe both the slip losses was introduced, highlighting that the energy consumption due to tire cornering is lower in motorcycles than in trucks or passenger vehicles. This latter result is due to the lean of the motorcycle into the curve, resulting in more lateral force provided by camber thrust instead of lateral tire deformation, which would imply higher sideslip angles.

The analysis of real-world data highlighted the inadequacy of standard driving cycles for high-performance motorcycles. The Sport Motorcycle Driving Cycle (SMDC) was developed using a stochastic approach to bridge this gap, achieving an error of -0.34% on consumption compared to real-world applications. The discrepancy between real-world data and the standard WMTC cycle suggests that more tailored driving cycles are necessary for accurate consumption predictions for this type of vehicle. Key metrics such as characteristic acceleration ($\bar{a}$) and aerodynamic speed (V_{aer}) were found to best describe fuel consumption and engine power, independent of vehicle parameters. The riding of sport motorcycles is characterized by an average speed not much higher than the standard cycles like WMTC part 2, but with harsher acceleration and deceleration. The developed methodology successfully generated high-fidelity driving cycles with an error lower than 1% in terms of characteristic acceleration and specific consumption. However, the study's limitation lies in the fact that data were gathered from internal combustion engine (ICE) motorcycles, which may not fully represent electric motorcycles dynamic behavior. Moreover, test riders covered only 387 km,

and the test riders might not align with typical riders. On the other hand, this approach could be very useful for design and testing purposes.

Gearbox losses were experimentally evaluated for two different powertrains, with findings indicating that free-driving losses are primarily linear speed-dependent. The difference in energy consumption between the two powertrains tested was substantial, with reductions of -29.2% and -35.8% for UDDS and WMTC cycles, respectively. Additionally, findings suggest that non-high-performance motorcycles may benefit from high-torque electric machines with fewer or no reduction stages, reducing transmission losses at the cost of increased mass and volume. This trade-off requires further investigation.

Regenerative braking on both wheels was analyzed using real-world data, considering different braking distributions (ρ) and road slopes. The study found that rear-wheel regenerative (RWR) architectures are preferable for standard driving cycles such as the WMTC due to their lower energy consumption, reduced complexity, and lower cost. Regenerative braking with two wheels (2WR) offered practically energy consumption independence from the brake distribution for all cycles investigated, which could be beneficial in high-performance riding scenarios. However, the impact of increased mass and inertia on vehicle handling must be assessed. The influence of road slope was also studied, revealing its effect on both energy consumption and braking force distribution.

A framework for sizing an electric two-wheel-driven motorcycle was developed, considering different regenerative braking architectures and their influence on consumption. The study jointly optimizes the force distribution between the wheels with the gear ratio, and rear motor and battery sizing, while explicitly considering vehicle dynamics and performance constraints joint optimize. The study confirmed that the optimal torque repartition strategy is generally more efficient in high-demand scenarios with aggressive riding conditions, despite working closer to the adherence limit. Whereas the ideal adherence strategy performed similarly for low-demand cycles, with significant difference on consumption (22,36%) in the Sport Motorcycle Driving Cycles, albeit the vehicle safety is maximized. The absence of thermal considerations and too simple battery modeling in the sizing process represents a limitation that should be addressed in future work. Finally, the gearbox mass and efficiency were considered independent of the gear ratio, and better models should be investigated to capture these aspects.

Overall, this study provides a solid foundation for the development of high-performance electric motorcycles by offering insights into driving cycle synthesis, powertrain losses, powertrain architecture, and regenerative braking strategies. The work combined a vehicle model and real-world data approach, allowing energy consumption analysis and powertrain architecture ranking. However, future work should focus on acquiring real-world data from electric motorcycles, integrating battery modeling, and considering thermal effects to refine the accuracy of the proposed models and methodologies.

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DATA ANALYSIS

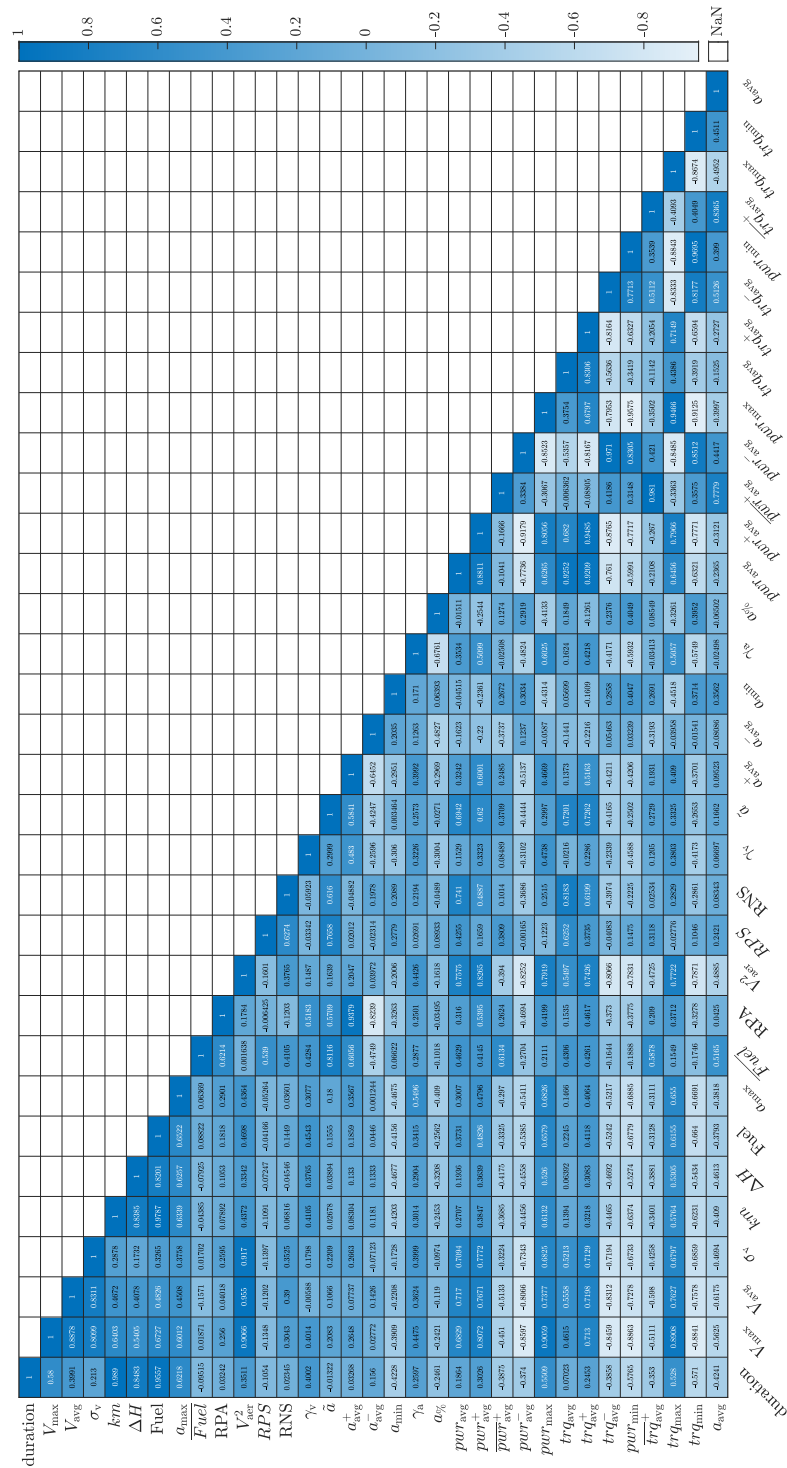


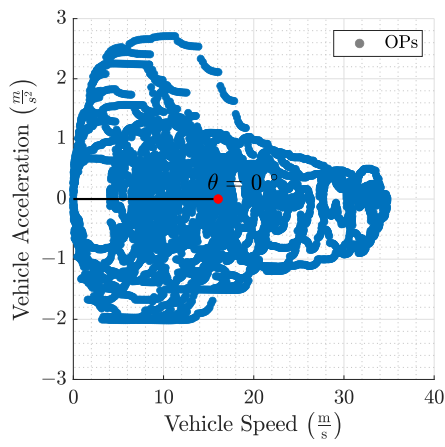
Figure 9.1: Pearson’s correlation coefficients for 33 features

POWERTRAIN SHIFT AND DRIFT

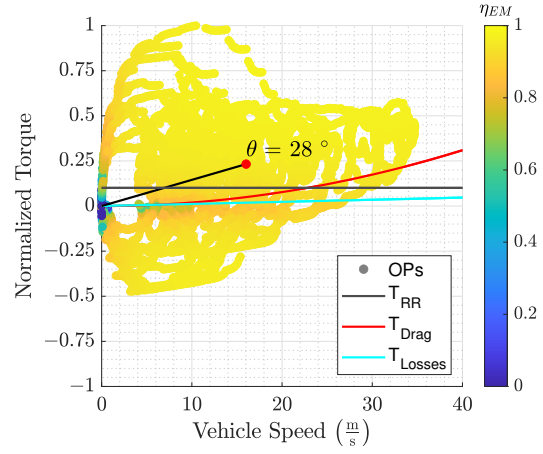
Mapping from the vehicle kinematic to the vehicle dynamics a shift and a speed drift on the operative points (OPs) are introduced. The shift is due to the speed-independent tire rolling resistance, while the speed drift is due to the aerodynamic and gearbox resistances. The overall shift and drift were described by θ as follows:

$$\tan(\theta) = \frac{\frac{\sum wa}{\sum w}}{\frac{\sum vw}{\sum w}} \quad 10.1$$

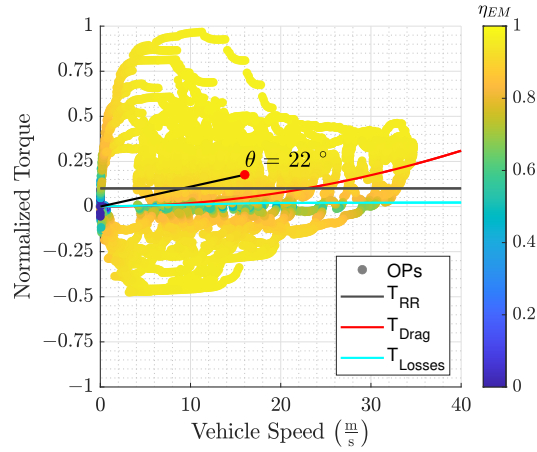
Where w are the weights values, v the speed values, and a the acceleration values. Choosing the weight as the motor efficiency gives the shift and drift at the battery, and choosing all the weights equals one, resulting in the vehicle dynamics shift and drift. In the latter condition, the angle θ represents the angle between the barycenter and the horizontal axes, as shown in Figure 10.1. In Figure 10.1a the center of mass is located on the horizontal axes because the average acceleration is zero, indeed the vehicle starts from zero speed and returns to zero speed. The location along the horizontal axes is the average speed, which is of course different from zero. Because of the single and constant gearbox speed reduction, the location along the x-axes did not change between the two models of gearboxes. While the torque needed to follow the speed profile was higher due to the higher gearbox loss. This can be seen by the higher θ value for powertrain A (28°) in Figure 10.1b compared to powertrain B (22°) in Figure 10.1c.



(a) WMTC kinematic.



(b) WMTC dynamic A.



(c) WMTC dynamic B.

Figure 10.1: (a) shows the vehicle kinematic points for the WMTC speed profile; (b) shows the motor operative points (OPs) for the powertrain A; (c) shows the motor operative points for the powertrain B. In these latter two subfigures, the color means the electric machine efficiency. The red dot in all the subfigures is the OPs barycenter and θ is the angle between the OPs barycenter and the horizontal axes (black line slope).



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