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May Allah send His blessings upon His noble Messenger, his family, and his companions, and may He bless us all in our lives.

Dedication

One of the greatest satisfactions in life is to offer ones success to the people we love.

I warmly dedicate this modest work to:

My dearest mother, for all the sacrifices, efforts, and support she has given me. I wish her good health and may ALLAH always protect her for me.

My beloved father, for his continuous efforts, guidance, and encouragement throughout all my years of study.

My dear sister and **my beloved brothers**.

All my family members, my classmates, and my friends with whom I have shared the best moments.

Abdelfetah Ouadah

الملخص

تُعدّ المركبات الكهربائية (EV) من أهم الحلول لتحقيق النقل المستدام. ومع ذلك، تواجه هذه المركبات تحديات كبيرة تتعلق بإدارة الطاقة والمراقبة الذكية لأنظمة البطاريات .يهدف هذا العمل إلى تطوير استراتيجيات فعّالة لتسيير الطاقة وأنظمة مراقبة متقدمة في المركبات الكهربائية الهجينة وتلك التي تعتمد على خلايا الوقود. يعتمد النهج المقترح على استخدام تقنيات الذكاء الاصطناعي (AI) وإنترنت الأشياء (IoT) لتحسين الكفاءة الطاقوية وضمان الموثوقية والأمان أثناء التشغيل .تمّ تصميم واختبار عدة استراتيجيات تحكم، مثل التحكم بالمنطق الضبابي وخوارزميات التحسين الجيني، بالإضافة إلى أساليب مراقبة تعتمد على التعلم الآلي .كما استُخدمت خوارزميات مثل K-means وRandom Forest لتقدير حالة شحن البطارية (SOC)وحالتها الصحية (SOH) بدقة عالية .تم تنفيذ المحاكاة باستخدام برنامج MATLAB/Simulink لتقييم الأداء من حيث كفاءة استهلاك الطاقة واستقرار النظام والكشف المبكر عن الأعطال. أظهرت النتائج أن دمج الذكاء الاصطناعي مع إنترنت الأشياء يساهم في تحسين الكفاءة، وإطالة عمر البطارية، وتعزيز الاستدامة في المركبات الكهربائية.

الكلمات المفتاحية :المركبات الكهربائية، تسيير الطاقة، الذكاء الاصطناعي، إنترنت الأشياء، المنطق الضبابي، مراقبة البطارية، الأنظمة الهجينة.

Abstract

Electric Vehicles have become a key solution for sustainable mobility, yet challenges persist in energy optimization and real-time monitoring. This thesis focuses on developing advanced energy management and intelligent monitoring strategies for hybrid and fuel cell electric vehicles. The proposed framework combines Artificial Intelligence and Internet of Things technologies to enhance energy efficiency, reliability, and safety.

Several control strategies are designed and evaluated, including fuzzy logicbased management, Genetic Algorithm optimization, and machine learningbased monitoring. The integration of K-means clustering and Random Forest classification enables accurate prediction of battery State of Charge and State of Health, while ensuring stable operation under dynamic driving conditions.

The developed models are simulated using MATLAB/Simulink to validate performance in terms of energy efficiency, battery stability, and fault prediction. The results demonstrate that combining AI-driven control and IoT-based monitoring significantly improves system adaptability and sustainability.

Keywords: *Electric Vehicles, Energy Management, Internet of Things, Artificial Intelligence, Fuzzy Logic, Battery Monitoring, Hybrid Systems.*

Résumé

Les véhicules électriques constituent aujourd’hui une solution essentielle pour une mobilité durable. Toutefois, des défis majeurs subsistent en matière d’optimisation énergétique et de surveillance en temps réel. Cette thèse propose le développement de stratégies avancées de gestion d’énergie et de surveillance intelligente pour les véhicules hybrides et à pile à combustible.

Le cadre méthodologique repose sur l'intégration de l'intelligence artificielle et de l'Internet des objets afin d'améliorer l'efficacité énergétique, la fiabilité et la sécurité des systèmes embarqués.

Plusieurs stratégies de contrôle ont été conçues et évaluées, notamment la gestion basée sur la logique floue, l'optimisation par algorithmes génétiques, ainsi que des approches de surveillance fondées sur l'apprentissage automatique. L'intégration des méthodes de regroupement K-means et de classification par forêts aléatoires permet d'estimer avec précision létat de charge et l'état de santé de la batterie, tout en assurant la stabilité du système dans des conditions de conduite variables.

Les modèles développés ont été simulés sous MATLAB/Simulink afin de valider les performances en termes defficacité énergétique, de stabilité de la batterie et de détection préventive des défauts. Les résultats montrent que la combinaison du contrôle intelligent basé sur lintelligence artificielle et de la surveillance connectée via lInternet des objets améliore significativement ladaptabilité, la durabilité et la performance globale des véhicules électriques.

Mots-clés : *Véhicules électriques, gestion d'énergie, Internet des objets, intelligence artificielle, logique floue, surveillance de batterie, systèmes hybrides.*

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General Conclusion and Perspectives **1**

List of Works

International Publications :

1. Ouadah, A., Merzouk, I., Hafaifa, A., Iratni, A., & Colak, I. (2025). *Enhancing Energy Efficiency for Sustainable Mobility in Fuel Cell Electric Vehicles via an Integrated Intelligent Energy Management System.* **Process Integration and Optimization for Sustainability**, 1–34.
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2. Ouadah, A., Merzouk, I., Hafaifa, A., Iratni, A. *Towards Efficient Energy Management in Parallel HEV : Comparative Study of Fuzzy Logic Strategies and Optimization Technique.*
Under review : –.–.–

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3. Abdelfetah Ouadah, Belgacem Said Khaldi, Leila Zemmouchi-Ghomari, Ahmed Hafaifa, Abdelhamid Iratni, Ilhami Colak. *Electric Vehicles : A Comprehensive Review of Types, Energy Management Strategies and Cost-effective for Sustainable Mobility.*
Under review : –.–.–

International/National Communications :

1. Ouadah, A., Khaldi, B. S., Iratni, A., & Hafaifa, A. (2023, December). Analysis of energy management and the environmental impact it has on electric vehicles : A comparative research and improvement opportunities. In 2023 **Second International Conference on Energy Transition and Security (ICETS)** (pp. 1-4). IEEE.
Published on : 05 February 2024

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2. Ouadah, A., Zemmouchi-Ghomari, L., Iratni, A., & Hafaifa, A. (2023, May). Dysfunctional Analysis of Electric Vehicles using the K-Nearest Neighbors Technique. In 2023 **1st International Conference on Renewable Solutions for Ecosystems : Towards a Sustainable Energy Transition (ICRSEtoSET)** (pp. 1-5). IEEE.
Published on : 14 May 2024

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3. Ouadah, A., Khaldi, B. S., Iratni, A., & Hafaifa, A. (2024, January). Analysis and Prediction of Electric Vehicle Costs : A Machine Learning-Based Approach. In 2024 ASU **International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)** (pp. 1-6). IEEE.
Published on : 19 March 2024

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4. Ouadah, A., Zemmouchi-Ghomari, L., Iratni, A., & Hafaifa, A. (22-11-2023). *Predictive Maintenance for Electric Vehicles : Advancing Sustainable and Efficient Mobility through IoT Integration.* **The First National Conference of Materials Sciences And Renewable Energy.**

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5. Ouadah, A., Mazouzi, A., Hafaifa, A. (May 27–28, 2025). *Fuzzy Logic Optimization for Energy Control in Parallel HEVs : A Simulation-Based Study.* **The 2nd WORKSHOP on Electric Vehicle Technology, May 27th–28th 2025.**

List of symbols

Symbol	Description	Unit
V_{bat}	Battery voltage	V
I_{bat}	Battery current	A
P_{bat}	Battery power	W
SOC	State of Charge	%
SOH	State of Health	%
E_{bat}	Stored energy in the battery	Wh
T_{bat}	Battery temperature	°C
R_{int}	Internal resistance of the battery	Ω
Q_{nom}	Nominal battery capacity	Ah
Q_{rem}	Remaining battery capacity	Ah
η_{bat}	Battery efficiency	-
V_{cell}	Single cell voltage	V
I_{cell}	Single cell current	A
N_{cell}	Number of cells in series	-
N_{mod}	Number of modules	-
P_{req}	Required power by the vehicle	W
P_{mot}	Motor power	W
P_{gen}	Generated power (from regenerative braking)	W
P_{loss}	Power losses in the system	W
T_{amb}	Ambient temperature	°C
t	Time	s
Δt	Time step	s
E_{in}	Energy input to the battery	Wh
E_{out}	Energy output from the battery	Wh
SOC_{min}	Minimum allowable SOC	%
SOC_{max}	Maximum allowable SOC	%
V_{max}	Maximum allowable voltage	V
V_{min}	Minimum allowable voltage	V
P_{AI}	AI- battery power or parameter	W
MSE	Mean Squared Error (for AI model evaluation)	-

R^2	Coefficient of determination (AI performance metric)	-
N	Number of samples or data points	-
f_s	Sampling frequency	Hz
R_{eq}	Equivalent resistance in circuit model	Ω
C_{eq}	Equivalent capacitance in circuit model	F
V_{oc}	Open-circuit voltage	V
I_{load}	Load current	A
T_{cell}	Cell temperature	°C
η_{conv}	Converter efficiency	-
$P_{loss,conv}$	Converter power losses	W
$P_{loss,heat}$	Power dissipated as heat	W
$SOC(t)$	State of Charge at time t	%
ΔSOC	SOC variation over time step	%
ΔE	Energy variation	Wh
P_{ICE}	Power of the internal combustion engine	W
P_{EM}	Power of the electric motor	W
P_{bat}	Battery power	W
P_{req}	Required power by the vehicle	W
T_{ICE}	Torque of the internal combustion engine	N.m
T_{EM}	Torque of the electric motor	N.m
T_{load}	Load torque	N.m
ω_{ICE}	Angular speed of the internal combustion engine	rad/s
ω_{EM}	Angular speed of the electric motor	rad/s
η_{ICE}	Efficiency of the internal combustion engine	-
η_{EM}	Efficiency of the electric motor	-
η_{bat}	Battery efficiency	-
V_{bat}	Battery voltage	V
I_{bat}	Battery current	A
SOC	State of Charge of the battery	%
SOC_{min}	Minimum allowable State of Charge	%
SOC_{max}	Maximum allowable State of Charge	%
ΔSOC	Variation in State of Charge	%
E_{bat}	Battery stored energy	Wh
E_{req}	Required energy demand	Wh
V_{veh}	Vehicle speed	km/h
a_{veh}	Vehicle acceleration	m/s^2
m_{veh}	Vehicle mass	kg
F_{trac}	Traction force	N
F_{res}	Resistive force (aerodynamic + rolling)	N
C_d	Aerodynamic drag coefficient	-

A_f	Frontal area of the vehicle	m^2
ρ_{air}	Air density	kg/m^3
g	Gravitational acceleration	m/s^2
C_{rr}	Rolling resistance coefficient	-
θ	Road angle	deg
$\dot{m}_{fuel}$	Fuel mass flow rate	g/s
Q_{LHV}	Lower heating value of fuel	MJ/kg
FC	Fuel consumption	L/100 km
HC	Hydrocarbon emissions	g/km
CO	Carbon monoxide emissions	g/km
NO_x	Nitrogen oxides emissions	g/km
PM	Particulate matter emissions	g/km
T_{amb}	Ambient temperature	°C
T_{bat}	Battery temperature	°C
$T_{ICE,max}$	Maximum torque of the ICE	N.m
$T_{EM,max}$	Maximum torque of the EM	N.m
W_{loss}	Power losses in the drivetrain	W
R_{int}	Internal resistance of the battery	Ω
P_{regen}	Regenerative braking power	W
E_{regen}	Energy recovered by regenerative braking	Wh
$SOC(t)$	Battery State of Charge at time t	%
E_{total}	Total energy consumption during the cycle	Wh
C_{fuel}	Fuel cost or fuel consumption cost function	-
C_{emiss}	Emission cost function	-
C_{total}	Total cost function (fuel + emission + battery usage)	-
w_1, w_2, w_3	Weighting factors in objective function	-
J	Objective or fitness function value	-
F_{fit}	Fitness function in Genetic Algorithm	-
N_{pop}	Population size in Genetic Algorithm	-
N_{gen}	Number of generations	-
P_c	Crossover probability	-
P_m	Mutation probability	-
$chrom_i$	i^{th} chromosome representing control parameters	-
G_{best}	Best solution (global optimum) found by GA	-
V_{ref}	Reference vehicle speed	km/h
P_{loss}	Power losses in the electrical converter	W
η_{conv}	Converter efficiency	-
P_{opt}	Optimized power split (ICE/EM)	W
λ	Lagrange multiplier (used for constraint handling)	-
μ	Membership function value in fuzzy system	-

α	Fuzzy scaling coefficient for input variables	-
β	Fuzzy scaling coefficient for output variables	-
e	Error input in fuzzy controller (e.g. SOC error)	-
Δe	Change of error input in fuzzy controller	-
u	Output control action from fuzzy controller	-
R^2	Coefficient of determination (model accuracy)	-
MSE	Mean Squared Error	-
N	Number of samples or data points	-
t	Time	s
Δt	Time step	s
V_{bat}	Battery voltage	V
I_{bat}	Battery current	A
T_{bat}	Battery temperature	°C
SOC	State of Charge of the battery	%
SOH	State of Health of the battery	%
R_{int}	Internal resistance of the battery	Ω
E_{bat}	Energy stored in the battery	Wh
P_{bat}	Battery power	W
Q_{nom}	Nominal capacity of the battery	Ah
Q_{rem}	Remaining capacity of the battery	Ah
T_{amb}	Ambient temperature	°C
V_{cell}	Voltage of a single cell	V
I_{cell}	Current of a single cell	A
N_{cell}	Number of cells in series	-
N_{mod}	Number of modules	-
P_{req}	Required power from the battery	W
P_{loss}	Power losses in the system	W
η_{bat}	Battery efficiency	-
SOC_{min}	Minimum allowable SOC	%
SOC_{max}	Maximum allowable SOC	%
V_{max}	Maximum allowable voltage	V
V_{min}	Minimum allowable voltage	V
E_{in}	Energy input to the battery	Wh
E_{out}	Energy output from the battery	Wh
P_{AI}	AI-predicted battery power or state variable	W
μ_i	Mean of the i^{th} variable (for normalization)	-
σ_i	Standard deviation of the i^{th} variable	-
Z_i	Normalized value (Z-score) of variable i	-
k	Number of clusters in K-means algorithm	-
$d(x_i, c_j)$	Euclidean distance between sample x_i and cluster center c_j	-

c_j	Cluster center of class j	-
J_k	Objective function of K-means clustering	-
n	Number of data points	-
MSE	Mean Squared Error (AI model metric)	-
R^2	Coefficient of determination (AI performance index)	-
y_i	Actual target value	-
$\hat{y}_i$	Predicted target value	-
$\bar{y}$	Mean of actual target values	-
N_{trees}	Number of decision trees in Random Forest	-
OOB	Out-of-Bag error estimate	-
f_{imp}	Feature importance (Random Forest metric)	-
t	Time	s
Δt	Time step	s
$SOC(t)$	State of Charge at time t	%
E_{total}	Total consumed energy during driving cycle	Wh
C_{data}	Collected dataset from battery sensors	-
N_{sample}	Number of samples in dataset	-
C_{cycle}	Driving cycle (e.g., FTP-75, US06, SC03, Highway)	-
V_{veh}	Vehicle speed	km/h
a_{veh}	Vehicle acceleration	m/s^2
P_{regen}	Regenerative braking power	W
E_{regen}	Regenerated energy during braking	Wh
T_{HIL}	Real-time Hardware-in-the-Loop simulation time	s

List of Abbreviations

AC	Air Conditioning
ADVISOR	Advanced Vehicle Simulator
AI	Artificial Intelligence
AFC	Alkaline Fuel Cell
ASM	Automotive Simulation Model
BEV	Battery Electric Vehicle
BMS	Battery Management System
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CYC_CBD14	Central Business District Driving Cycle
DC-AC	Direct Current to Alternating Current Converter (Inverter)
DC-DC	Direct Current to Direct Current Converter
DMFC	Direct Methanol Fuel Cell
DNN	Deep Neural Network
dSPACE	Digital Signal Processing and Control Engineering (hardware supplier)
ECU	Electronic Control Unit
EDLC	Electric Double-Layer Capacitor
EM	Energy Management
EMS	Energy Management Strategy
EMSys	Energy Management System
EREV	Extended-Range Electric Vehicle
ESS	Energy Storage System
EV	Electric Vehicle
FC	Fuel Cell
FC-HEV / FCHV	Fuel Cell Hybrid Electric Vehicle / Fuel Cell Hybrid Vehicle
FCEV	Fuel Cell Electric Vehicle
FEM	Fuzzy Energy Management
FEMO	Fuzzy Energy Management Optimized
FFM	Fuzzy Fuel Minimization
FLCS	Fuzzy Logic Control Strategy
FTP-75	Federal Test Procedure Urban Driving Cycle (USA)

GA	Genetic Algorithm
G2V	Grid-to-Vehicle
GPS	Global Positioning System
HC	Hydrocarbons
HEV	Hybrid Electric Vehicle
HIL	Hardware-in-the-Loop
HWFET	Highway Fuel Economy Test Cycle
ICE	Internal Combustion Engine
IoT	Internet of Things
Ibat	Battery Current
LiB / Li-ion	Lithium-ion Battery
LTE-M	Long-Term Evolution for Machines
MCFC	Molten Carbonate Fuel Cell
ML	Machine Learning
ModelDesk	dSPACE tool for vehicle and road configuration
MotionDesk	dSPACE tool for 3D visualization of simulations
MQTT	Message Queuing Telemetry Transport
MPC	Model Predictive Control
M2M	Machine-to-Machine
NB-IoT	Narrowband Internet of Things
NiCd	Nickel-Cadmium Battery
NiMH	Nickel-Metal Hydride Battery
NO_x	Nitrogen Oxides
NREL	National Renewable Energy Laboratory
OOB	Out-of-Bag (validation method in Random Forest)
PAFC	Phosphoric Acid Fuel Cell
PEMFC	Proton Exchange Membrane Fuel Cell
PHEV	Plug-in Hybrid Electric Vehicle
PM	Particulate Matter
PV	Photovoltaic
RC	ResistorCapacitor (model for supercapacitor)
RF	Random Forest
RFID	Radio-Frequency Identification
RL	Reinforcement Learning
R&D	Research and Development
SC	Supercapacitor
SC03	Supplemental Federal Test Procedure Air Conditioning Cycle (USA)
SMES	Superconducting Magnetic Energy Storage
SOC / SoC	State of Charge
SOH / SoH	State of Health

SOFC	Solid Oxide Fuel Cell
Tbat	Battery Temperature
UEC	Unified Electrochemical Converter
UDDS	Urban Dynamometer Driving Schedule
UC	Ultracapacitor
US06	Supplemental Federal Test Procedure High-Speed/High-Load Cycle (USA)
V2G	Vehicle-to-Grid

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General Introduction

1. Context and Motivation

The rapid transition towards sustainable mobility has positioned Electric Vehicles (EVs) as a cornerstone of future transportation systems. By replacing conventional internal combustion engines with electrified powertrains, EVs offer a cleaner, more efficient, and environmentally responsible alternative that addresses global concerns related to greenhouse gas emissions and fossil fuel depletion [36].

Despite their increasing adoption, EVs continue to face significant technical challenges, notably in terms of energy storage limitations, charging infrastructure, real-time energy optimization, and long-term battery reliability[72]. These aspects make energy management and battery monitoring crucial research areas to ensure the reliability, safety, and efficiency of electric mobility [65].

2. Problem Statement

At the heart of these challenges lies the **Energy Management System (EMS)**, which governs the optimal distribution of power between various components, including the battery, electric motor, auxiliary loads, and, in hybrid configurations, secondary energy sources such as fuel cells or internal combustion engines [43].

A well-designed EMS improves driving range and efficiency while protecting the battery from deep discharges, overcharging, and thermal stress. However, the management process remains complex due to highly dynamic conditions (driving cycles, road topography, load variations, temperature)[43].

In parallel, battery monitoring presents another challenge. Accurate estimation of parameters such as **State of Charge (SOC)**, **State of Health (SOH)**, current, voltage, and temperature is essential for performance and safety. Yet, traditional monitoring systems struggle to process large-scale, heterogeneous, and time-varying data in real time [64].

Therefore, there is a clear need for an integrated and intelligent framework capable of managing energy and monitoring batteries simultaneously under uncertain and dynamic conditions [72]. At the heart of these challenges lies the **Energy Management System (EMS)**, which governs the optimal distribution of power between various components, including the battery, electric motor, auxiliary loads, and, in hybrid configurations, secondary energy sources such as

fuel cells or internal combustion engines.

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Therefore, there is a clear need for an integrated and intelligent framework capable of managing energy and monitoring batteries simultaneously under uncertain and dynamic conditions.

3. Research Objectives

The main objective of this thesis is to investigate and develop advanced methodologies for **energy management and monitoring in electric vehicles**, leveraging IoT technologies and AI-based techniques.

The specific objectives are as follows:

- Develop intelligent **energy management strategies** based on fuzzy logic and evolutionary algorithms to optimize energy flow in hybrid architectures.
- Design an **AI- and IoT-enabled framework** for real-time data acquisition, monitoring, and control of EV components.
- Propose **machine learning models** for accurate estimation and classification of battery states (SOC, SOH, operational modes).
- Validate the proposed approaches through **simulation-based studies** using standard driving cycles and performance indicators.

4. Main Contributions

The main contributions of this thesis can be summarized as follows:

- A comprehensive analysis of energy management strategies for different EV configurations, including hybrid and fuel-cell systems.
- Development of fuzzy logic-based EMS strategies, optimized using Genetic Algorithms (GA) for improved efficiency and SOC stability.
- Integration of IoT and AI concepts for intelligent energy monitoring and predictive battery management.

- Implementation of data-driven models (K-means clustering, Random Forest) for battery classification and fault prediction.

- Publications derived from this research:

  1) Ouadah, A., Merzouk, I., Hafaifa, A., Iratni, A., & Colak, I. (2025). *Enhancing Energy Efficiency for Sustainable Mobility in Fuel Cell Electric Vehicles via an Integrated Intelligent Energy Management System.* **Process Integration and Optimization for Sustainability**, 134.
     Published on: 27/06/2025

  2) Ouadah, A., Merzouk, I., Hafaifa, A., Iratni, A. *Towards Efficient Energy Management in Parallel HEV: Comparative Study of Fuzzy Logic Strategies and Optimization Technique.*
     Under review : –.–.–

  3) Abdelfetah Ouadah, Belgacem Said Khaldi, Leila Zemmouchi-Ghomari, Ahmed Hafaifa, Abdelhamid Iratni, Ilhami Colak. *Electric Vehicles: A Comprehensive Review of Types, Energy Management Strategies and Cost-effective for Sustainable Mobility.*
     Under review : –.–.–

5. Thesis Organization

This thesis is structured into five chapters as follows:

- **Chapter 1** provides a foundational overview of electric vehicles and their energy management requirements. It introduces different EV categories and highlights the pivotal role of EMS in improving performance and sustainability.

- **Chapter 2** discusses the integration of **IoT and AI** in EV energy management and monitoring, emphasizing data-driven control, predictive maintenance, and smart charging.

- **Chapter 3** examines **Fuel Cell Electric Vehicles (FCEVs)** and hybrid architectures, evaluating EMS algorithms for optimal power distribution.

- **Chapter 4** focuses on **fuzzy logic-based EMS** for Hybrid Electric Vehicles, complemented by optimization through Genetic Algorithms to achieve energyemission trade-offs.

- **Chapter 5** addresses **battery monitoring and classification** using K-means clustering and Random Forest models for accurate state estimation and predictive analysis.

To provide a clear understanding of the logical flow and interconnections among the different parts of this work, the overall organization of the thesis is illustrated in Figure 1.

This diagram shows the sequential development of the research from the foundational study of EV architectures to the design, optimization, and intelligent monitoring of energy systems emphasizing how each chapter contributes to the proposed integrated framework.

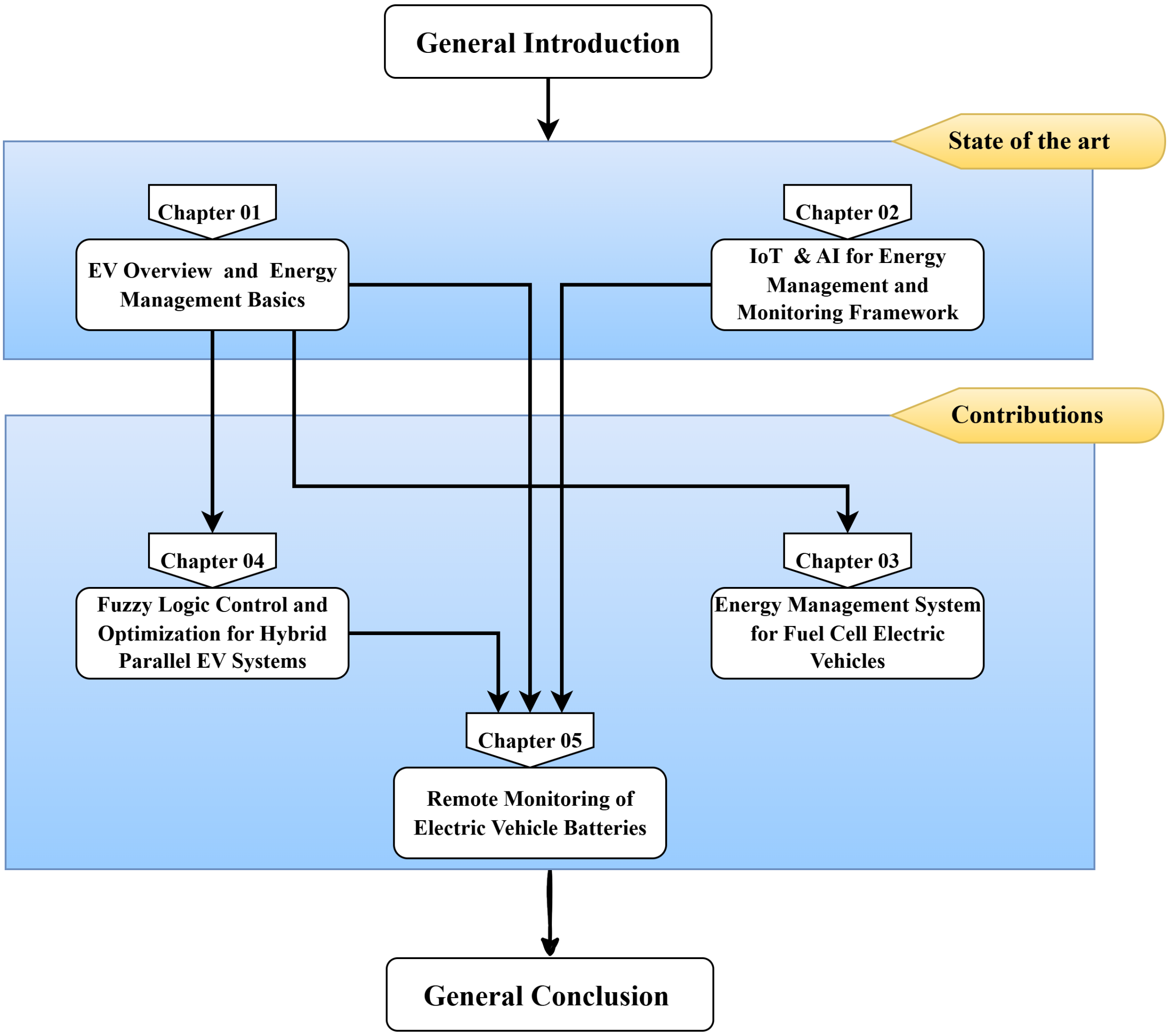

Figure 1: General schematic of the thesis structure

Chapter I

An Overview of Electric Vehicles and Their Energy Management

I.1 Introduction

The global transportation sector is undergoing a profound transformation driven by the urgent need to reduce greenhouse gas emissions, improve energy efficiency, and transition toward cleaner mobility solutions. Within this context, electric vehicles (EVs) have emerged as a cornerstone of sustainable transportation, offering an environmentally friendly alternative to conventional internal combustion engine vehicles. Their growing adoption reflects both technological advancements in energy storage and conversion systems, as well as international policies promoting low-carbon mobility. However, the large-scale deployment of EVs introduces new scientific and engineering challenges, particularly regarding energy management, battery performance, and system integration.

At the core of every electric vehicle lies the Energy Management System (EMS), a crucial component responsible for ensuring the optimal distribution of power among various subsystems such as the battery, electric motor, and auxiliary loads. The EMS must dynamically adapt to varying driving conditions, user demands, and environmental factors to maintain both efficiency and reliability. Effective energy management directly influences the driving range, vehicle performance, and battery lifespan, making it a key determinant of EV viability and competitiveness.

Given these considerations, this chapter provides a comprehensive overview of electric vehicle fundamentals and their associated energy management requirements. It examines the main EV architecturesincluding Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), Fuel Cell Electric Vehicles (FCEVs), and Extended-Range Electric Vehicles (EREVs)and discusses their comparative advantages, limitations, and fields of application. The objective is to establish a solid foundation for understanding how different configurations influence power flow, energy storage, and efficiency, thereby preparing the groundwork for the advanced topics addressed in subsequent chapters, such as intelligent and IoT-based energy management.

I.2 Electric Vehicles

Electric vehicles (EVs) have a comprehensive and evolving history, dating back to before the year 2000 and achieving commercial success until approximately 1918. In their initial years, EVs were extensively utilized; however, the swift progression and widespread adoption of gasoline-powered internal combustion engines (ICE) precipitated their decline, with electric automobiles nearly vanishing by 1933. This transition was chiefly attributable to ICE vehicles exhibiting greater speed, lower costs, and technological advantages at that period. Notwithstanding this decline, the fundamental issues responsible for the EV's early competitive edgesuch as battery limitations and elevated costsremained unaddressed for many decades [56].

Significant progress in power electronics and microelectronics has paved the way for a new generation of electric powertrains, enabling contemporary electric vehicles (EVs) to compete with internal combustion engine vehicles in terms of performance. Although challenges persist in battery energy storage, innovative manufacturing techniques and materials are consistently advancing the capabilities of battery systems. This technological progression has reignited interest in electric vehicles, driven by factors such as rising energy costs, the need for energy independence, and a growing commitment to environmental conservation. As gasoline supplies become increasingly limited and costly, the adoption of electric vehicles is being viewed more favorably as a sustainable solution. EVs are capable of harnessing power from diverse renewable sources and are frequently recharged during periods of excess utility capacity, thereby further enhancing their environmental benefits [16].

The remarkable conversion efficiency of electric motorsfrequently nearing 100% renders EVs significantly more efficient than traditional vehicles, whose ICEs generally attain only 3040% efficiency. Research such as 'tank-to-wheel efficiency' emphasizes the superior power transmission capabilities of EVs and their beneficial role in reducing greenhouse gas emissions. Broader environmental considerations, including the potential for substantially lower urban air pollution and zero emissions at the point of use, have established electric vehicles as a crucial component of national policies aimed at promoting safer, more efficient, and sustainable transportation [18].

The term "**Electric Vehicle**" encompasses not only fully electric models but also those equipped with an electric motor that supplies part of the propulsion. This distinction includes various vehicle types, each exhibiting differing levels of autonomy and emissions profiles. To comply with contemporary CO2 emission standards, some vehiclesparticularly the heavier variantsincorporate light hybrid technology, reflecting the diverse technological landscape available today. Currently, electric vehicles are classified into four main categories: BEVs, HEVs ,PHEVs, and FCEVs, each with distinct capabilities and environmental impacts. Overall, these advancements demonstrate ongoing developments in electric vehicle technology, underscoring their historical significance, engineering progress, and broad spectrum of modern manifestations [11].

I.3 Electric Vehicle Typologies

Electric vehicles (EVs) have become a fundamental component in the transition towards sustainable transportation, as they employ electric propulsion powered by various energy storage systems such as chemical batteries, fuel cells, supercapacitors, and kinetic energy storage devices (such as flywheels). The classification of EVs primarily depends on the methods used to store and restore energy. The most prevalent categories include BEVs, HEVs, PHEVs, FCEVs, and EREVs, as illustrated in Figure I.1. Each category possesses distinct technological features, operational advantages, and structural constraints, which are discussed herein [42].

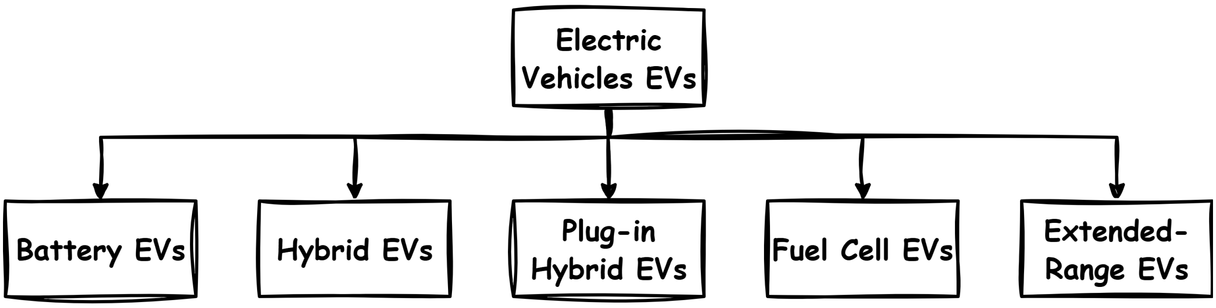

Figure I.1: Electric vehicle categories.

I.3.1 Battery Electric Vehicles (BEVs)

Battery Electric Vehicles are the most straightforward category of electric vehicles, operating exclusively on electricity without an internal combustion engine . These vehicles rely on substantial battery packs, typically providing ranges between 160 and 300 km. Nonetheless, more sophisticated models are capable of surpassing 500 km on a single charge. Innovations, such as electric motors integrated directly into the wheel hubs, have contributed to weight and size reduction, thereby enhancing efficiency and enabling more versatile designs [11, 56]. The absence of conventional moving mechanical components also improves system reliability, reduces noise levels, and minimizes maintenance requirements, thereby extending the vehicle's operational lifespan. The general structure of a Battery Electric Vehicle is illustrated in Figure I.2, highlighting the main components such as the battery pack, electric motor, power electronics, and charging system. An exemplary model in this category is the **Nissan Leaf, equipped with a 62-kWh battery that delivers a range of up to 360 km [39, 55].

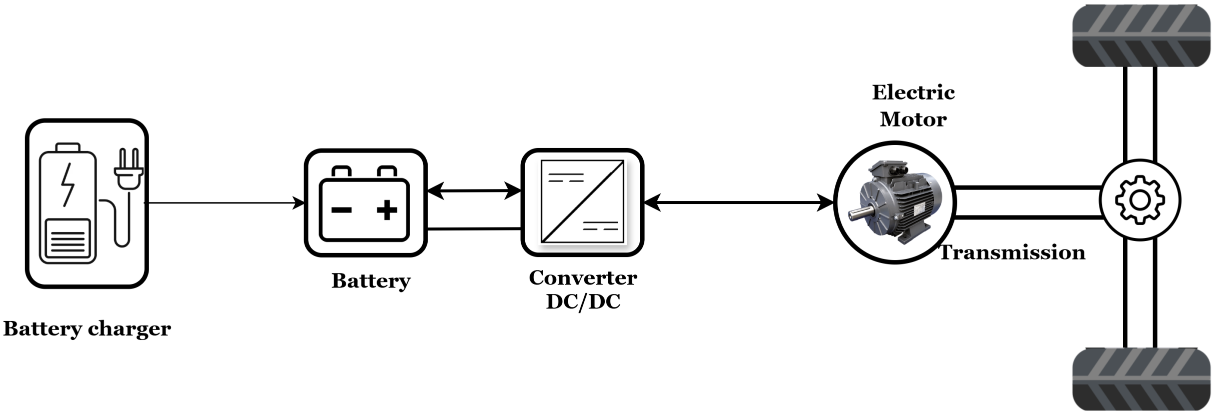

Figure I.2: BEV configuration.

I.3.2 Hybrid Electric Vehicles (HEVs)

Hybrid Electric Vehicles (HEVs) integrate electric and combustion propulsion systems to enhance energy efficiency and address the limitations of BEVs, such as limited driving range, higher battery costs, and prolonged charging times. Unlike plug-in hybrids, HEVs are incapable of being charged directly from the grid; instead, their batteries are maintained through regenerative braking and the energy produced by the ICE [39, 56]. From a technological perspective, HEVs are classified into three primary types: series, parallel, and series-parallel hybrids [41, 60].

In series HEVs, the ICE functions solely as a generator to produce electricity for the traction motor, thereby separating it from the transmission system. This configuration improves ICE efficiency but introduces additional complexity and potential conversion losses [46]. The general structure of series HEV is illustrated in Figure I.3.

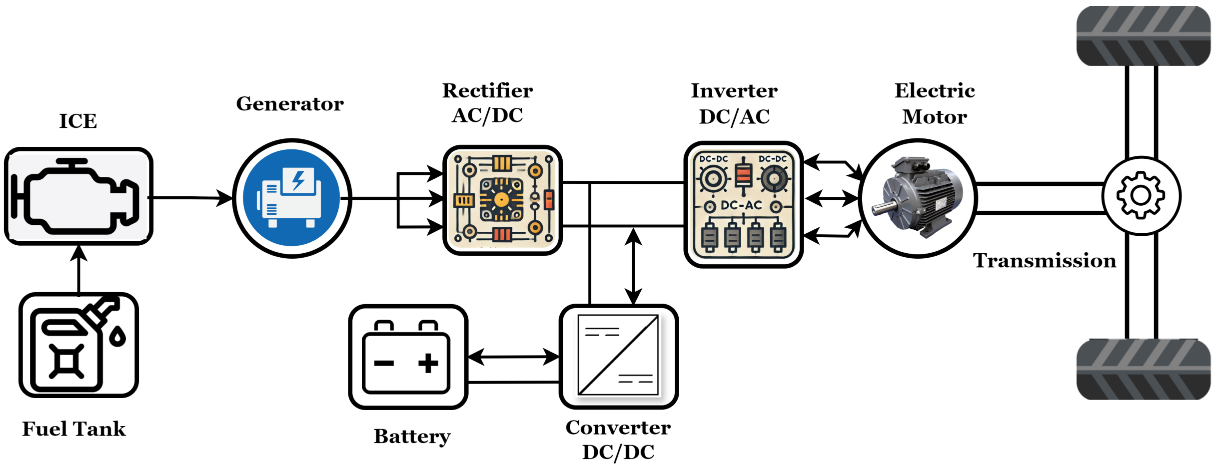

Figure I.3: ICE-based series-HEV configuration.

Parallel HEVs connect both the ICE and the motor to the transmission, thereby reducing the motor's size requirement and minimizing energy losses. However, this approach complicates system design and maintenance [58]. The general structure of a parallel HEV is illustrated in Figure I.4.

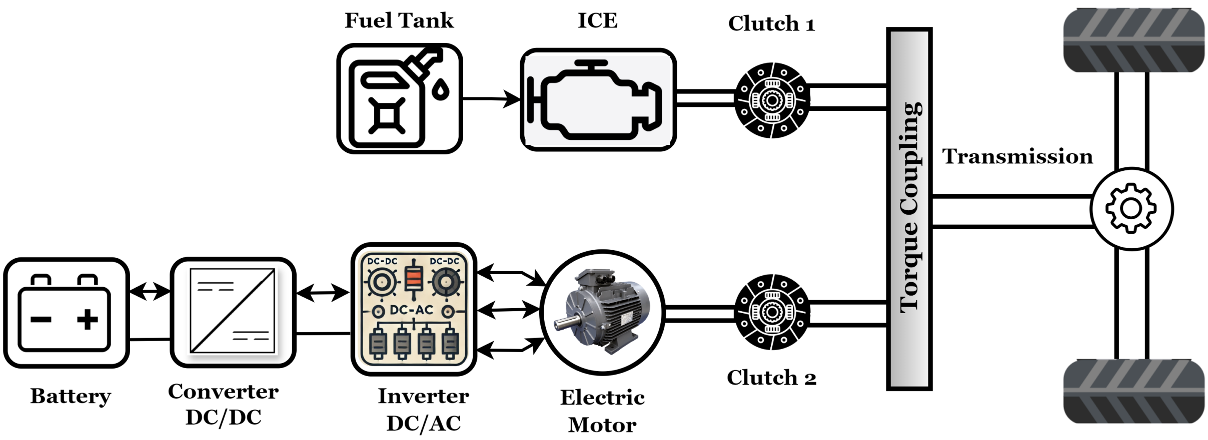

Figure I.4: ICE-based parallel-HEV configuration.

The series-parallel configuration amalgamates features of both, providing operational flexibility at the expense of increased structural complexity and weight [48]. The general structure of a series-parallel HEV is illustrated in Figure I.5.

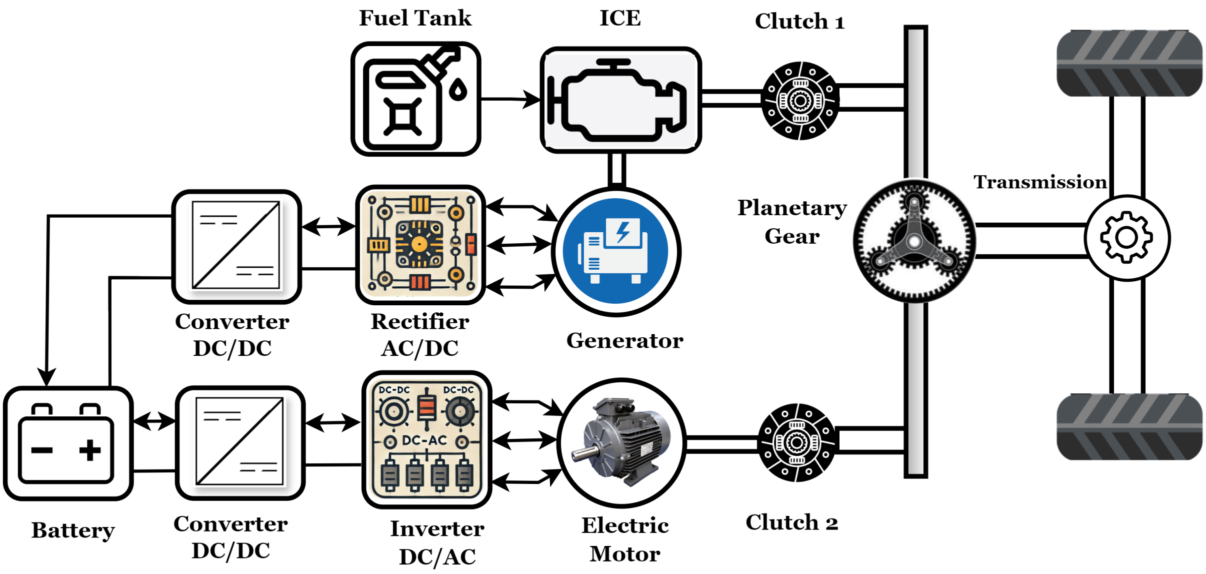

Figure I.5: ICE-based series-parallel HEV configuration (complex type).

The commercial success of HEVs is exemplified by models such as the Toyota Prius and Honda Insight, with manufacturers including Toyota, Nissan, and Lexus increasingly favouring the series-parallel architecture in recent designs.

I.3.3 Plug-in Hybrid Electric Vehicles (PHEVs)

Plug-in Hybrid Electric Vehicles were introduced as an evolutionary advancement over conventional HEVs, primarily designed to improve electric driving range through the facilitation of external recharging of larger battery packs [39, 56]. While traditional HEVs sustain charge via regenerative braking and support from an ICE, PHEVs permit grid-based charging, thereby diminishing reliance on fuel sources. Nonetheless, the incorporation of larger batteries introduces technical challenges related to thermal management, safety, and cost, as well as necessitating additional power electronics and converters for efficient energy transfer [52, 60].

The configurations described in the HEV are similarly employed in the PHEV, with the sole distinction being the EV chargers, which constitute the only additional option relative to the preceding configuration. The overall architecture of a PHEV is depicted in Figure I.6.

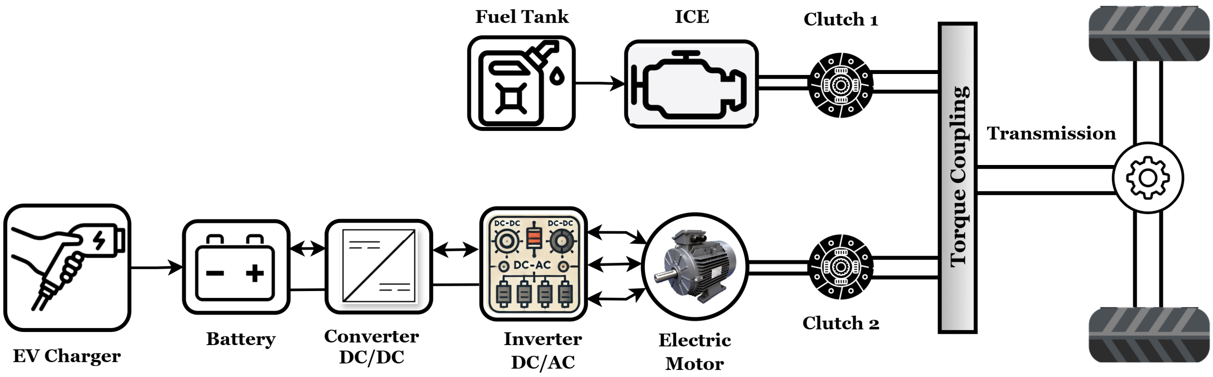

Figure I.6: Parallel PHEV using ICE technology.

An illustrative example is the Mitsubishi Outlander PHEV, equipped with a 12-kWh battery that offers approximately 50 kilometers of pure electric driving. However, empirical studies indicate that PHEVs frequently consume more gasoline than manufacturer specifications suggest, partly attributable to variations in driving patterns and charging behaviors. This discrepancy underscores the importance of scrutinizing manufacturer claims and considering driver behavior in evaluating vehicle performance efficiency [47].

I.3.4 Fuel Cell Electric Vehicles (FCEVs)

Fuel Cell Electric Vehicles utilize hydrogen fuel cells as their primary energy source, thereby distinguishing them from battery-operated electric vehicles. Recent advancements in fuel cell technology have enhanced their potential as alternatives to ICE vehicles [56, 67]. Despite their promise, the broader adoption of FCEVs remains dependent on cost reduction, improved energy efficiency, and the development of an adequate hydrogen refuelling infrastructure. Current forecasts indicate that FCEVs could achieve widespread adoption after 2030, provided these challenges are effectively addressed [39, 67]. The general structure of an FCEV is illustrated in Figure I.7.

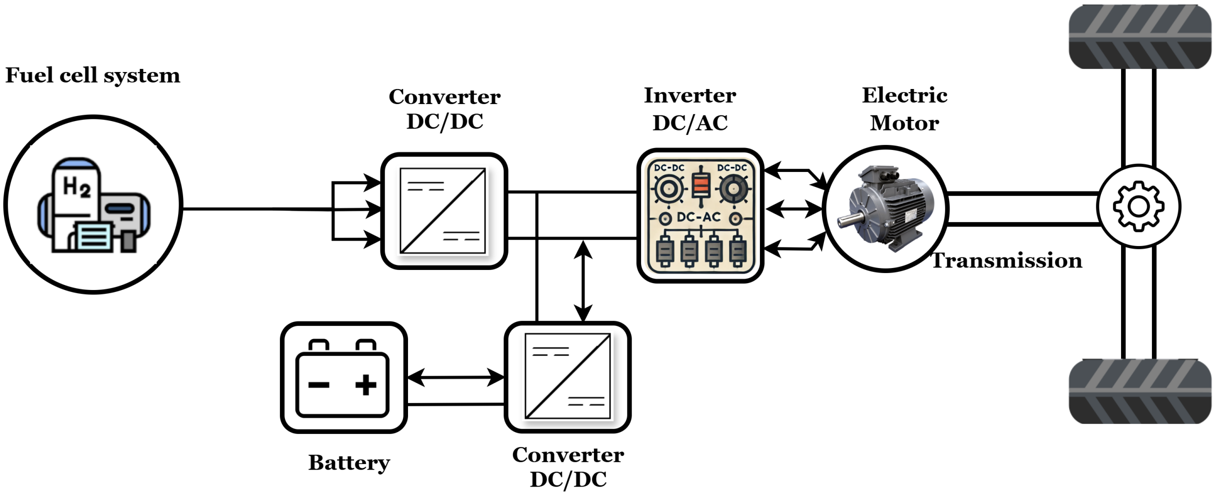

Figure I.7: Fuel Cell-EV configuration.

I.3.5 Extended-Range Electric Vehicles (EREVs)

EREVs occupy a transitional position between BEVs and PHEVs. Similar to BEVs, they primarily depend on stored electrical energy; however, they are equipped with a small auxiliary combustion engine functioning solely as a generator to recharge the battery. Unlike in PHEVs or HEVs, the auxiliary power unit in an EREV is not mechanically linked to the drivetrain. This configuration maintains the operational simplicity characteristic of BEVs while alleviating range anxiety [67]. The general structure of an FCEV is illustrated in Figure I.8. A notable example is the **BMW i3**, which incorporates a 42.2 kWh battery providing an approximate electric range of 260 km, supplemented by an additional 130 km in extended-range mode [16].

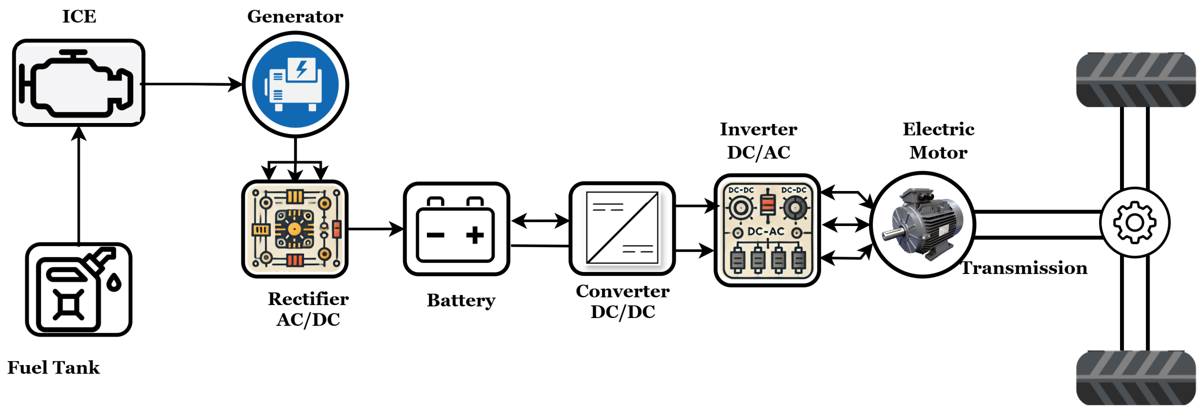

Figure I.8: Extended-Range-EV configuration.

Various types of electric vehicles possess distinct advantages and limitations. BEVs emit no tailpipe pollutants and are suitable for short- and medium-distance travel; however, they face challenges related to charging infrastructure and battery manufacturing. PHEVs benefit from an extended driving range and low emissions in electric mode; however, they still rely on both electric charging and traditional fuel refueling. FCEVs offer longer ranges and rapid refueling capabilities; however, progress is hindered by the limited and costly infrastructure for hydrogen. HEVs provide improved fuel efficiency; however, they are not zero-emission and continue to depend on fossil fuels. The high costs associated with electric and hybrid vehicles remain a significant obstacle to their widespread adoption.

To facilitate the transition towards a sustainable transportation system, it is essential to employ a diverse mix of these electric vehicle types, complemented by advancements in recharging infrastructure, renewable energy generation, battery technology, and vehicle lifespan extension. Ongoing research and development efforts, supported by effective policies and customer satisfaction strategies, are crucial for overcoming the challenges faced by each vehicle type and promoting their widespread adoptionthus contributing to the reduction of greenhouse gas emissions and supporting the global effort to combat climate change.

I.3.6 Comparison of EVs' traits and features

The automotive sector is undergoing a transitional phase characterized by the diversification of engine types to accommodate emerging energy sources and environmental requirements. Various technologies enabling coexistence in vehiclesincluding traditional thermal engines, fully electric solutions, hybrid variants, and fuel cellsare progressively expanding. These technologies vary in terms of carburetor type, technological complexity, energy storage options, and intended operational domain (urban or highway). Table I.1 & Table I.2 summarize a comparative analysis of the primary vehicle types, considering factors such as energy source availability, technological advancements, and limitations.

Table I.1: Comparative Analysis of Automotive Propulsion Technologies

Types of EVs	**Fuel type**	**Efficiency**	**Driving range**	**Structure**	**ESS**	**Overall cost**	**Driving mode**
ICE	Gasoline	Low	High	Simple	Fuel tank	High	City and highway
BEVs	Electric	High	Low	Simple	Battery and ultracapacitor	Low	City
HEVs	Gasoline + Electric	Low	Medium	Medium	Ultracapacitor, battery, and fuel tank	Medium	City and highway
PHEVs	Gasoline + Electric	High	High	Complex	The battery, ultracapacitor, and fuel tank may all be charged using an outlet.	Medium	City and highway
FCEVs	FC + SC/Battery	High	High	Complex	a hydrogen-powered fuel cell	High	City and highway
EREVs	Gasoline + Electric	High	Medium	Medium	Battery and ultracapacitor, Fuel tank	Medium	City

The comparative analysis presented in Table I.1 reveals the increasing diversity of automotive propulsion systems and highlights the technological evolution driven by environmental and energy challenges. Internal combustion engine vehicles remain the most widespread due to their technological maturity, mechanical simplicity, and long driving range. However, their high fuel consumption and pollutant emissions make them less sustainable in the current context of energy transition. On the other hand, BEVs stand out for their high efficiency and zero-emission operation, although their limited autonomy and long recharging times restrict their suitability mainly to urban applications. Hybrid architectures, including HEVs, PHEVs, and EREVs, emerge as intermediate solutions that balance the advantages of both electric and thermal propulsion systems. Finally, FCEVs represent a promising alternative for future mobility, offering high energy efficiency and low environmental impact, but still facing challenges related to cost, durability, and hydrogen infrastructure deployment.

Table I.2: Comparison of Electric Vehicle Types: Advantages and Disadvantages

Types of EVs	**Advantages**	**Disadvantages**
ICE	1. Advanced technologies 2. Increased effectiveness 3. It's easy and dependable 4. Industry-driven	1. Negative emissions 2. Poor fuel effectiveness
BEVs	1. Pollution-free 2. Efficient 3. Relatively mature technology	1. Ineffective dynamic response 2. Prolonged recharging
HEVs	1. Minimal emissions 2. Good fuel efficiency 3. Dependable and robust	1. Bulky 2. There are more components.
PHEVs	1. Very energy-efficient 2. Minimal emissions 3. The ability of V2G or G2V 4. Quiet and efficient performance	1. Expensive initial cost 2. Grid impact
FCEVs	1. Clean of pollution 2. Greater energy effectiveness 3. Perform silently and smoothly.	1. Developing technology 2. Expensive and inadequate security
EREVs	1. Low emission 2. Efficient 3. The small size of the heat engine.	1. The noise 2. The vibrations altered

Table I.2 further reinforces these observations by outlining the strengths and weaknesses of each vehicle category. ICE vehicles demonstrate reliability and industrial maturity, but contribute significantly to greenhouse gas emissions. In contrast, BEVs and FCEVs offer clean, efficient propulsion, yet high production costs, storage limitations, and limited infrastructure availability constrain them. Hybrid configurations, such as HEVs and PHEVs, offer a practical compromise by reducing emissions and optimizing fuel consumption without sacrificing performance, making them particularly relevant during this transitional phase toward full electrification. Overall, this comparative discussion underscores the need to develop advanced energy management and optimization strategies to enhance vehicle efficiency, extend driving range, and support the global shift toward sustainable, intelligent mobility systems.
In conclusion, the comparative analysis of vehicle propulsion technologies highlights a transitional phase in the automotive industry, where traditional ICEs coexist with various electrified solutions such as BEVs, HEVs, PHEVs, FCEVs, and EREVs. Each technology has its natural strengths and limitations, making it suitable for specific use cases. BEVs perform best in urban environments, hybrids offer balanced efficiency, and advanced systems, such as FCEVs

and EREVs, show long-term promise despite current costs and infrastructure hurdles. This variety highlights the absence of a single, universal solution, underscoring the ongoing need for technological complementarity to achieve both performance and sustainability objectives.

I.4 Energy Management Strategies

Energy Management Strategies (EMS) are a fundamental component of electric and hybrid vehicle operation, encompassing methodologies, algorithms, and control techniques that regulate and optimize energy consumption across different power sources. Their central purpose is to ensure a balanced and intelligent distribution of energy between key components such as batteries, fuel cells, electric motors, and, in the case of HEVs, internal combustion engines. By efficiently coordinating these energy flows, EMS contributes to improved fuel economy, reduced emissions, and extended lifespan of both the energy storage system and the overall powertrain.

The design of an effective EMS remains a complex challenge, as it must reconcile multiple and often conflicting objectives while maintaining computational efficiency for real-time implementation. An ideal EMS must simultaneously enhance system performance, guarantee driver comfort, and adapt dynamically to varying driving conditions, traffic situations, and user behaviors. The primary objectives of an EMS include:

- Minimizing fuel and overall energy consumption;
- Reducing pollutant emissions and environmental impact ;
- Enhancing global system efficiency and responsiveness ;
- Maintaining the batterys State of Charge (SOC) within safe operational limits;
- Prolonging the lifetime of the energy storage system (ESS);
- Ensuring vehicle drivability and user comfort;
- Adapting control actions to diverse driving cycles and environmental conditions

Rather than focusing solely on energy consumption optimization, a well-designed EMS seeks to establish an optimal trade-off between efficiency, sustainability, and system reliability. To achieve this, various approaches have been developed, ranging from rule-based and fuzzy-logic control to optimization-based and machine-learning-driven strategies. Each of these techniques offers distinct benefits in terms of adaptability, computational complexity, and accuracy. The following sections present a comparative overview of these strategies, emphasizing their principles, implementation methods, and relevance to different electric and hybrid vehicle architectures.

I.5 Main Categories of EMS

EMS can generally be classified into three principal categories based on their methodology and complexity levels.Figure I.9 [34] illustrates the categorization of standard EMS techniques.

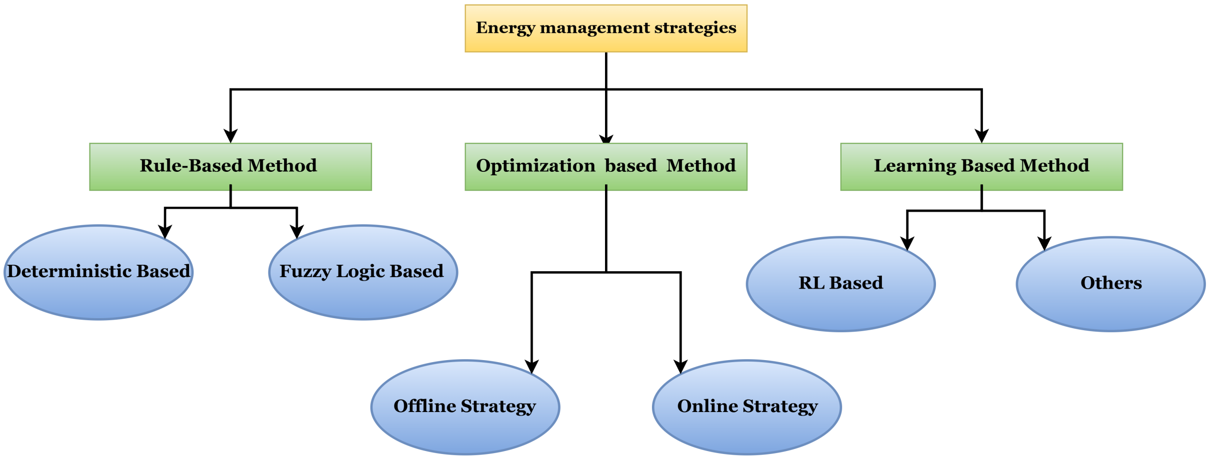

Figure I.9: Classification of Energy Management Strategies.

I.5.1 Rule-Based EMS

The Rule-Based EMS relies on predefined rules formulated through engineering expertise, test data, or heuristic knowledge. In practice, it functions by switching priorities according to driving conditions; for instance, prioritizing the electric motor in urban settings and engaging the ICE for highway driving. Its primary advantages are simplicity, low computational requirements, and dependable real-time performance. However, its limited flexibility restricts its ability to adapt to unanticipated driving scenarios, often resulting in sub-optimal performance under dynamic conditions [25, 48].

I.5.2 Optimization-Based EMS

The Optimization-Based EMS approaches energy management as a mathematical optimization problem aimed at minimizing fuel consumption, emissions, cost, or powertrain degradation. A variety of methods are employed, including dynamic programming, quadratic programming, evolutionary algorithms, and model predictive control (MPC). This approach can accommodate multiple objectives and generate robust, near-optimal results, rendering it highly adaptable to complex systems. Nevertheless, its practical application is constrained by high computational costs, the necessity for precise system models, and challenges associated with real-time implementation [20, 75].

I.5.3 Learning-Based EMS

The Learning-Based EMS utilizes Artificial Intelligence techniques, including neural networks (NN) and Reinforcement Learning (RL). By leveraging historical driving data and real-time sensor inputs, it can continuously adapt and optimize energy distribution policies. Its greatest strengths lie in its adaptability and capacity to predict and optimize across a broad spectrum of conditions, making it particularly suitable for future intelligent and autonomous vehicles.

However, its effectiveness is contingent upon the availability of extensive training datasets, substantial computing power, and complex real-time integration, which remain challenging [25, 34].

I.5.4 Comparison of EMS characteristics and features

To critically evaluate the applicability of various EMS for hybrid and electric powertrains, it is essential to conduct a systematic comparison across several key dimensions. These include design complexity, computational burden, adaptability to diverse operating conditions, achievable performance, and dependence on system data or models. Such a comparative framework (Table I.3) enables a more precise assessment of the trade-offs inherent in Rule-Based, Optimization-Based, and Learning-Based approaches, thereby providing valuable insights into their practical suitability for current applications and their potential for future advancements.

Table I.3: Comparative Analysis of Energy Management Strategies.

Criteria	**Rule-Based EMS**	**Optimization-Based EMS**	**Learning-Based EMS**
Design complexity	Low	Medium to high	High
Computational load	Very low	High	Medium to very high
Adaptability	Low	Medium	Very high
Overall performance	Moderate (often suboptimal)	Near-optimal (if accurate models)	Potentially optimal (if well-trained)
Real-time robustness	High	Medium (depends on fast methods)	Medium to high (depends on training)
Data dependency	None	High (system model needed)	Very high (large datasets required)
Typical use cases	Standard hybrid vehicles	R&D, advanced hybrid prototypes	Intelligent/autonomous vehicles

In summary, the comparative analysis reveals that each Energy Management Strategy has distinct strengths and limitations that impact its suitability for various contexts. Rule-Based EMS remains the most practical choice in the short term for commercial applications, where robustness and simplicity are prioritized over peak performance. Conversely, Optimization-Based EMS delivers near-optimal solutions and is particularly advantageous during the design and development stages when adequate computational resources are accessible. Looking forward, Learning-Based EMS demonstrates the most promise, providing adaptability and predictive capabilities that align with the requirements of intelligent and autonomous vehicles. Nonetheless, further advancements in data availability, computational efficiency, and system integration are necessary before this approach can be broadly implemented.

I.6 Conclusion

The initial chapter highlights the growing importance of electric vehicles as integral components of the transition to sustainable mobility, emphasizing their role in reducing the environmental impact of transportation. It delineates various categories of electric vehiclesincluding BEVs , HEVs, PHEVs, FCEVs, and EREVs illustrates how technological diversity signifies ongoing innovation designed to meet diverse needs for autonomy, flexibility, and energy source integration. Each category provides distinct advantages but also encounters specific challenges, such as constraints related to energy storage, operational complexity, or infrastructure requirements.

Concurrently, the chapter examines the pivotal role of Energy Management Systems (EMSys) in enhancing vehicle performance and energy efficiency. EMS strategieswhether conventional or advancedmust be tailored to the vehicle's design and real-world operational conditions. This underscores the necessity for customized solutions over generic approaches to manage energy resources and reduce emissions effectively.

In sum, this chapter establishes a foundational understanding of the interplay between electric vehicle design and energy management strategies, which is essential for future research endeavors. This integrated perspective will be instrumental in addressing the technical, economic, and environmental challenges associated with the expansion of electric mobility. A collective comprehension of vehicle architectures and EMS methodologies will facilitate breakthroughs in sustainable transportation and energy management.

Chapter II

Integration of IoT and Artificial Intelligence for Advanced Energy Management in Electric Vehicles

II.1 Introduction

The Internet of Things (IoT) and Artificial Intelligence (AI) represent two transformative technologies that are rapidly reshaping the contemporary transportation landscape, particularly within the domain of electric vehicles (EVs). IoT facilitates the connection of vehicles to communicate in real-time with other vehicles, infrastructural elements, and cloud services, thereby enabling more intelligent decision-making and operational efficiency. Concurrently, AI equips vehicles with the ability to learn from data, perceive their surroundings, and autonomously optimize driving and energy management behaviors.

Electric vehicles, which constitute a crucial component of sustainable transportation, have become increasingly intelligent through the integration of IoT and AI. These vehicles employ IoT-connected sensors and devices to monitor parameters such as battery health, driving conditions, and traffic patterns. AI algorithms analyze these data to optimize battery utilization, predict maintenance requirements, and adjust driving modes to enhance energy efficiency and extend the operational range.

Moreover, AI-powered energy management systems within EVs facilitate the seamless integration of renewable energy sources and dynamic charging strategies. For instance, AI can coordinate vehicle charging during off-peak periods or when renewable energy availability is at its peak, thereby reducing costs and environmental impact.

The synergistic application of IoT and AI in electric vehicles not only enhances the driving experience through personalization and safety features but also significantly contributes to the development of smart grids and sustainable energy systems. Intelligent energy management supports grid stability by orchestrating vehicle charging and discharging processes, resulting in a more resilient and efficient power network.

This chapter explores advanced technologies that integrate IoT and AI for electric vehicles, with particular emphasis on applications in energy management, autonomous driving, and predictive maintenance. Additionally, key challenges and future research directions are addressed to foster innovations in intelligent and sustainable mobility solutions.

II.2 Internet of Things

The Internet of Things (IoT) represents a transformative paradigm in modern information and communication technologies, enabling seamless interaction between the digital and physical worlds. To fully understand its significance, it is first important to acknowledge its origins within the broader evolution of the Internet [19, 75]. Beginning with the first experimental computer networks of the 1960s, followed by the invention of the Internet in the 1970s, the commercialization of online services in the 1980s, and the emergence of the World Wide Web in 1989, global connectivity has continually advanced. The proliferation of mobile Internet in the 1990s and the subsequent development of social networks in the early 2000s further extended digital interconnectivity from systems and devices to people. The IoT represents the next stage in this evolution, where not only humans but also objects, machines, and environments are integrated into a global communication framework [27, 30].

Conceptually, the IoT combines two fundamental elements: the "Internet" the global interconnection of devices through standardized protocols (TCP/IP) - and "Things" physical or virtual entities uniquely identifiable within this infrastructure. In this regard, IoT can be defined as a vast, dynamic, and distributed network of intelligent objects capable of sensing, identifying, processing, and communicating autonomously. These objects utilize embedded technologies, including sensors, actuators, RFID tags, GPS modules, and smart devices, enabling real-time data collection, information exchange, and coordinated decision-making across diverse contexts [17, 32].

This diversity of interactions enabled by the Internet of Thingsconnecting any person, any object, at any time and place, across various networks and servicesbridges the physical, digital, and virtual worlds, as illustrated in Figure II.1.

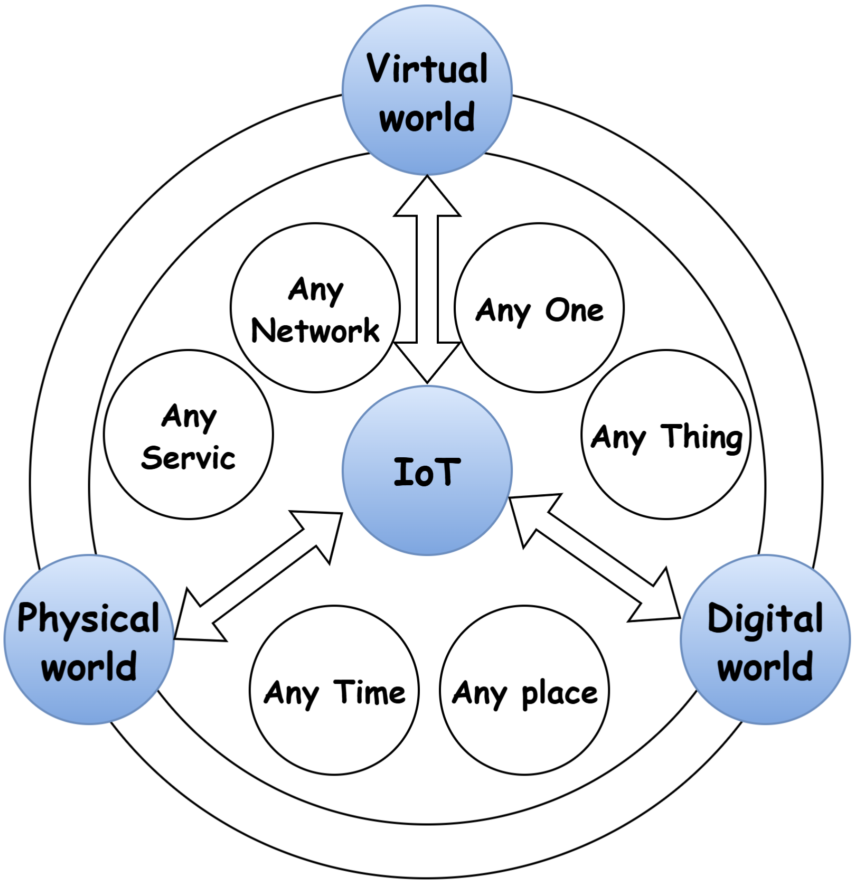

Figure II.1: Conceptual representation of the Internet of Things (IoT)[9].

Beyond its technological foundations, the IoT is expected to have a profound impact on the global economy. It is projected that the economic impact of IoT will range from USD 2.7 trillion to 6.2 trillion by 2025, driven by the proliferation of IoT devices that are critical to emerging applications and machine-type communications [12]. Figure II.2 illustrates the top 10 IoT application areas where this technology is already transforming industries and enhancing the quality of life, including healthcare, smart homes, smart cities, manufacturing, and transportation.

The healthcare sector, in particular, is expected to experience annual global economic growth of between USD 1.1 trillion and USD 2.5 trillion by 2025, driven by IoT-enabled innovations. Currently, the number of Internet-connected devices exceeds the human population and is projected to continue growing rapidly. By 2024, it is estimated that 45% of all Internet traffic will consist of machine-to-machine (M2M) communications, enabled by smart sensors and actuators that transmit data and coordinate decisions without human intervention.

However, while each IoT device on its own consumes relatively little power, the collective energy demand of billions of devices, coupled with the data processing needs of large data centers, creates significant sustainability challenges. In response, a new research field known as "Green IoT" has emerged, focused on enhancing the energy efficiency and reducing the carbon footprint of IoT systems throughout their lifecyclefrom design and deployment to operation and maintenance [7].

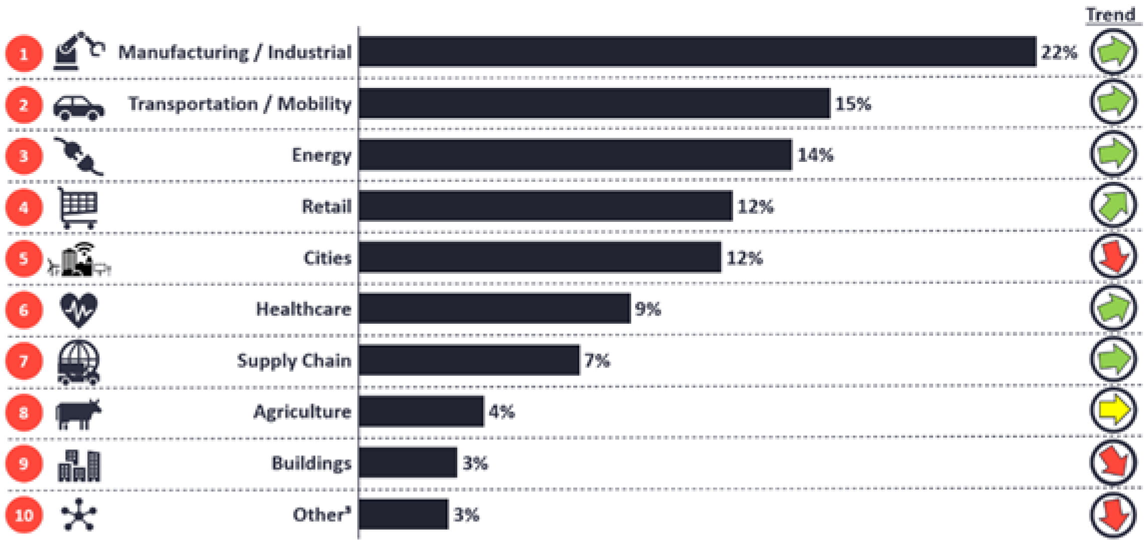

Figure II.2: Top 10 IoT application areas in 2020[9]

The Green IoT initiative aims to develop advanced methods and technologies to lower power consumption and promote eco-sustainability, ensuring the responsible growth of IoT ecosystems. Addressing these energy concerns will be crucial as the IoT continues to expand across various sectors and geographies, underscoring the need for innovative solutions that strike a balance between performance and environmental impact [21].

II.3 IoT Technologies for EV Energy Management: The Foundation of Connectivity

IoT technologies form the foundation for innovative EV energy management. They provide the essential infrastructure for thorough data collection, reliable communication, and seamless interaction with external systems, ensuring EVs operate at optimal efficiency and integrate smoothly into the larger energy network [23, 31].

II.3.1 IoT Sensors and Real-Time Data Acquisition: The Vehicle's Pulse

Modern EVs are equipped with an array of sophisticated IoT sensors that continuously monitor a multitude of parameters. These sensors are vital for understanding the vehicle's dynamic state and ensuring optimal energy utilization. Key measurements include the battery's State of Charge (SoC), State of Health (SoH), voltage, current, and temperature. Additionally, sensors track the charging status, motor performance, and environmental conditions, including ambient temperature and humidity [37].

This real-time data is critical for several functions:

- **Battery Health Monitoring:** Sensors detect subtle changes in battery performance, identifying potential degradation or abnormalities that could impact lifespan or safety.

For instance, precise temperature monitoring prevents overheating during charging or discharge, a common cause of battery degradation.

- **Dynamic Charging Management:** Real-time data informs the Battery Management System (BMS) to dynamically adjust charging rates based on battery temperature, SoC, and grid conditions, optimizing efficiency and preventing damage.

- **Energy Consumption Tracking:** By monitoring energy flow to various components, the system can provide accurate insights into energy consumption patterns, which is crucial for range prediction and driving efficiency.

The ability to acquire and process this data in real-time enables proactive adjustments and timely interventions, thereby maximizing both vehicle performance and longevity. Figure II.3 illustrates the typical sensor placement within an Electric Vehicle, highlighting its extensive data collection capabilities.

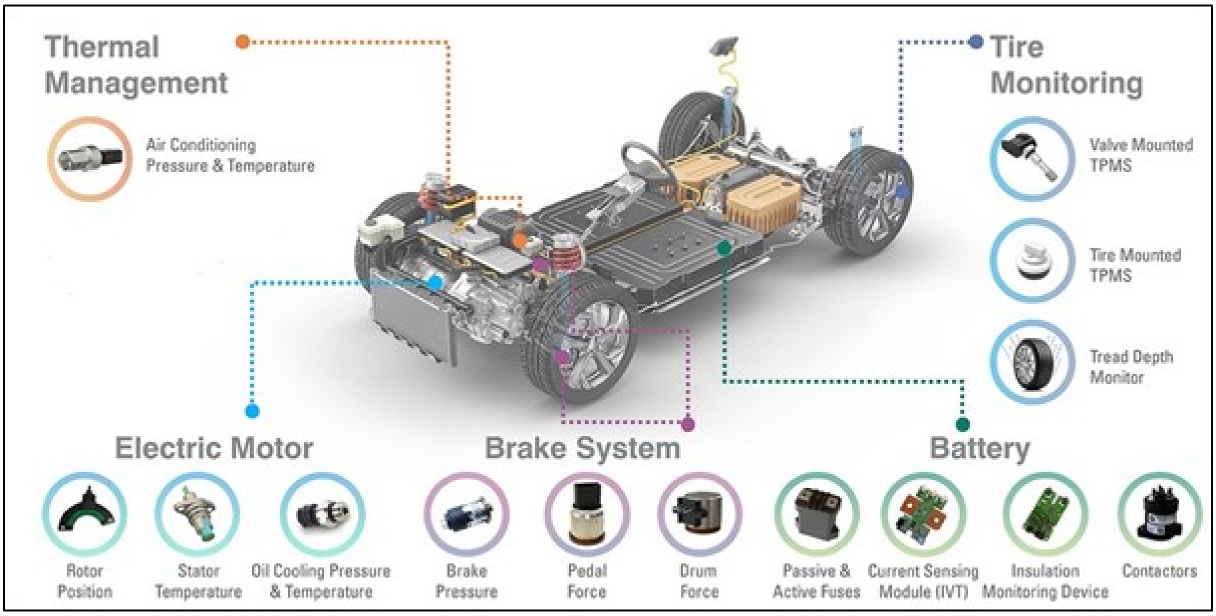

Figure II.3: Illustration of typical sensor placement within an Electric Vehicle.

II.3.2 Communication Protocols and IoT Architectures: The Data Superhighway

Effective electric vehicle energy management relies on resilient communication protocols and sophisticated IoT architectures. These systems facilitate secure and scalable data exchange among vehicles, charging infrastructure, and cloud platforms. Standard protocols encompass Cellular IoT technologies such as LTE-M and NB-IoT to ensure broad connectivity, as well as MQTT for lightweight messaging, thereby guaranteeing efficient and reliable data transmission [57].

The architectures often employ a hybrid approach, combining edge computing with cloud-based systems:

- **Edge Computing:** Local processing of data near the source (e.g., within the vehicle or at the charging station) allows for real-time decision-making, reducing latency for critical operations like dynamic power adjustments or immediate fault detection.
- **Cloud Platforms**: For long-term storage, comprehensive analytics, and fleet-wide optimization, data is aggregated and processed in the cloud. This enables insights into long-term trends, predictive maintenance, and strategic energy management.

This layered approach ensures both rapid response times for immediate needs and deep analytical capabilities for strategic planning. Figure II.4 illustrates a conceptual diagram of an EV charging station integrated into a broader network.

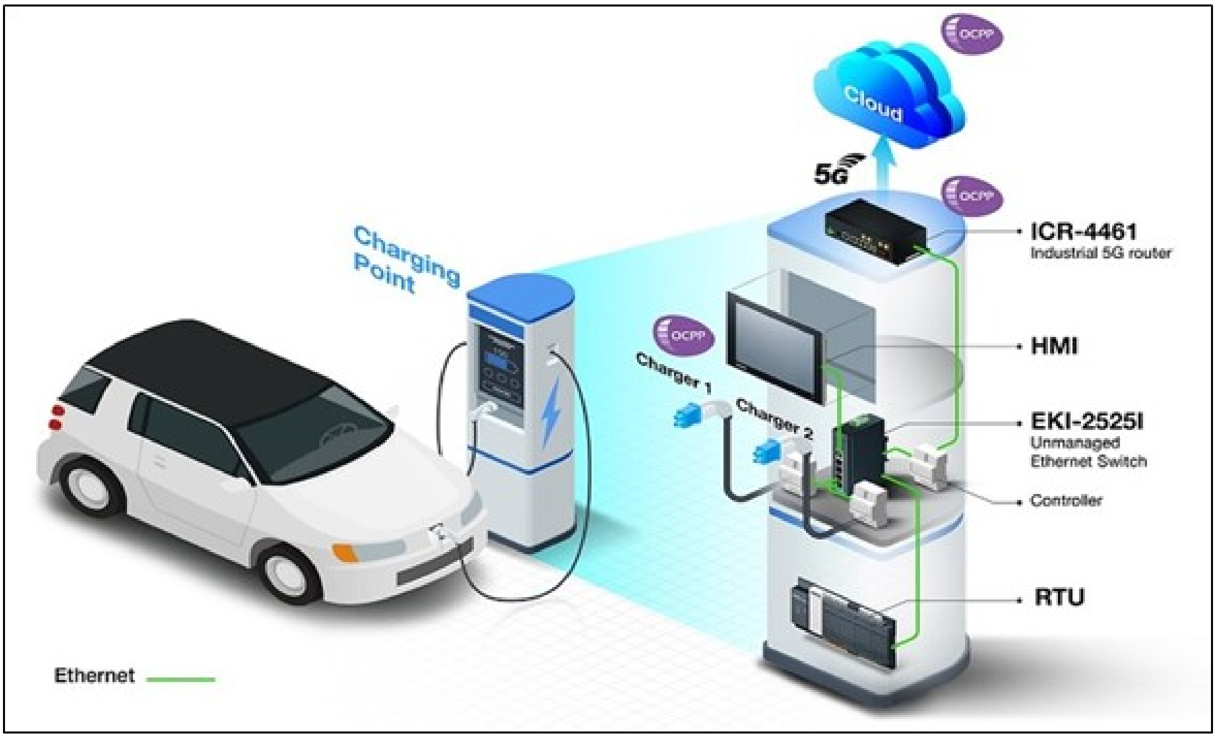

Figure II.4: A conceptual diagram illustrating the integration of an EV charging station into a broader network.

II.3.3 Interaction and Connectivity with Infrastructures: Beyond the Vehicle

IoT's true power in EV energy management extends to its ability to connect EVs with external infrastructures. This connectivity is crucial for optimizing charging, balancing grid loads, and even transforming EVs into active participants in the energy market [59].

- **Smart Charging Stations:** IoT enables bi-directional communication between EVs and charging stations. This enables features such as automatic charging initiation, dynamic load balancing (which distributes power efficiently among multiple charging vehicles), and scheduled charging to take advantage of off-peak electricity rates.

- **Smart Grids and V2G (Vehicle-to-Grid) Technology:** Integration with smart grids allows EVs to not only consume energy but also to supply energy back to the grid during peak demand or when renewable energy sources are intermittent. This V2G capability enhances grid stability, supports the integration of renewable energy, and can offer economic benefits to EV owners.
- **Fleet Management:** For commercial EV fleets, IoT provides centralized monitoring and management capabilities, optimizing routes, charging schedules, and maintenance for entire fleets, leading to significant operational efficiencies and cost savings.

II.4 Artificial Intelligence for EV Energy Optimization: The Brains Behind the Power

Artificial Intelligence leverages the vast datasets collected by IoT systems to transform them into actionable insights and intelligent optimizations. AI algorithms learn from historical data and real-time inputs to predict, adapt, and refine energy management strategies, pushing EVs towards unprecedented levels of efficiency and autonomy.

II.4.1 AI Algorithms for Battery Charge and Discharge Optimization: Extending Lifespan and Range

AI plays a pivotal role in dynamically optimizing the delicate processes of battery charging and discharging. Machine learning models analyze historical battery performance, degradation patterns, and environmental factors to devise optimal charging protocols [13]. This includes:

- **Adaptive Charging:** AI can adjust charging rates and profiles in real-time based on battery temperature, SoH, and even electricity tariffs. This ensures faster charging without compromising battery longevity and allows for cost-effective charging during off-peak hours [33].
- **Discharge Management:** AI optimizes power distribution within the EV during driving, ensuring efficient energy utilization for propulsion and ancillary systems. This can include intelligent energy flow between the battery and electric motors, improving overall mileage.
- **Cycle Optimization:** By predicting the impact of different charge/discharge cycles on battery degradation, AI can recommend strategies that extend the battery's useful life while meeting the driver's needs.

II.4.2 Predictive Maintenance Based on IoT Data: Proactive Care for Peak Performance

One of the most significant applications of AI in conjunction with IoT is predictive maintenance. Instead of reactive repairs or scheduled maintenance, AI models analyze continuous streams of sensor data to predict potential failures before they occur.

- **Early Fault Detection:** AI can identify subtle anomalies in sensor readingssuch as unusual temperature fluctuations in battery cells, changes in motor vibrations, or voltage irregularitiesthat indicate nascent issues.
- **Component Health Forecasting:** By learning from past data, AI models can forecast the degradation of critical components, particularly the battery pack, providing insights into its remaining useful life.
- **Reduced Downtime and Costs:** This proactive approach allows for timely interventions, minimizing unexpected breakdowns, reducing repair costs, and ensuring higher vehicle availability. For example, a predictive maintenance system might alert an owner to a potential issue with a battery module weeks before it becomes critical, allowing for scheduled servicing.

II.4.3 Real-Time Energy Optimization Strategies via AI: Adaptive Driving and Beyond

AI enables dynamic, real-time management of energy cycles within the EV, adapting to changing conditions and driver behavior to maximize efficiency [**?**]. This includes:

- **Energy Management (EM) Cycles:** AI can manage the power flow to different vehicle components (electric motors, climate control, infotainment) based on driving conditions, route topography, and real-time traffic. For example, it can optimize regenerative braking to capture maximum energy in stop-and-go traffic.
- **Adaptive Driving:** AI-powered systems can provide real-time recommendations or even subtly adjust vehicle parameters to encourage energy-efficient driving. This might involve optimizing acceleration and deceleration profiles, managing cruise control settings, or suggesting optimal speeds.
- **Route-Based Optimization:** AI integrates with navigation systems to analyze routes, elevation changes, and predicted traffic patterns to optimize energy consumption throughout the journey, identifying the most energy-efficient path.

II.4.4 Range Prediction and Dynamic Energy Consumption Management: Eliminating Range Anxiety

One of the most common concerns for EV owners is "range anxiety." AI significantly mitigates this by providing highly accurate range predictions and dynamically managing energy consumption.

- **Accurate Range Prediction:** AI models factor in a multitude of variableshistorical driving patterns, current battery SoC, ambient temperature, terrain, traffic conditions, and even driver behaviorto provide a much more precise estimate of remaining range than traditional methods.

- **Dynamic Route Planning:** Based on range predictions, AI can dynamically suggest optimal charging points along a route, or even modify the route to ensure the driver reaches their destination with sufficient charge.

- **Adaptive Consumption:** If the estimated range becomes critical, AI can intelligently manage auxiliary systems (e.g., reducing climate control intensity) to conserve energy and extend the driving distance, providing timely alerts to the driver.

II.5 Benefits and Challenges of Integrating IoT and AI in EV Energy Management

The integration of the Internet of Things (IoT) and Artificial Intelligence (AI) in Electric Vehicle (EV) energy management represents a major technological leap toward intelligent, efficient, and sustainable mobility. To better illustrate this convergence, several critical factors can be analyzed on a comparative scale. The radar chart below (Figure II.5) presents a synthesized analysis of how different dimensions of EV energy managementsuch as data utilization, predictive maintenance, control precision, and energy efficiencyare influenced by traditional, IoT-enhanced, and AI-enhanced systems.

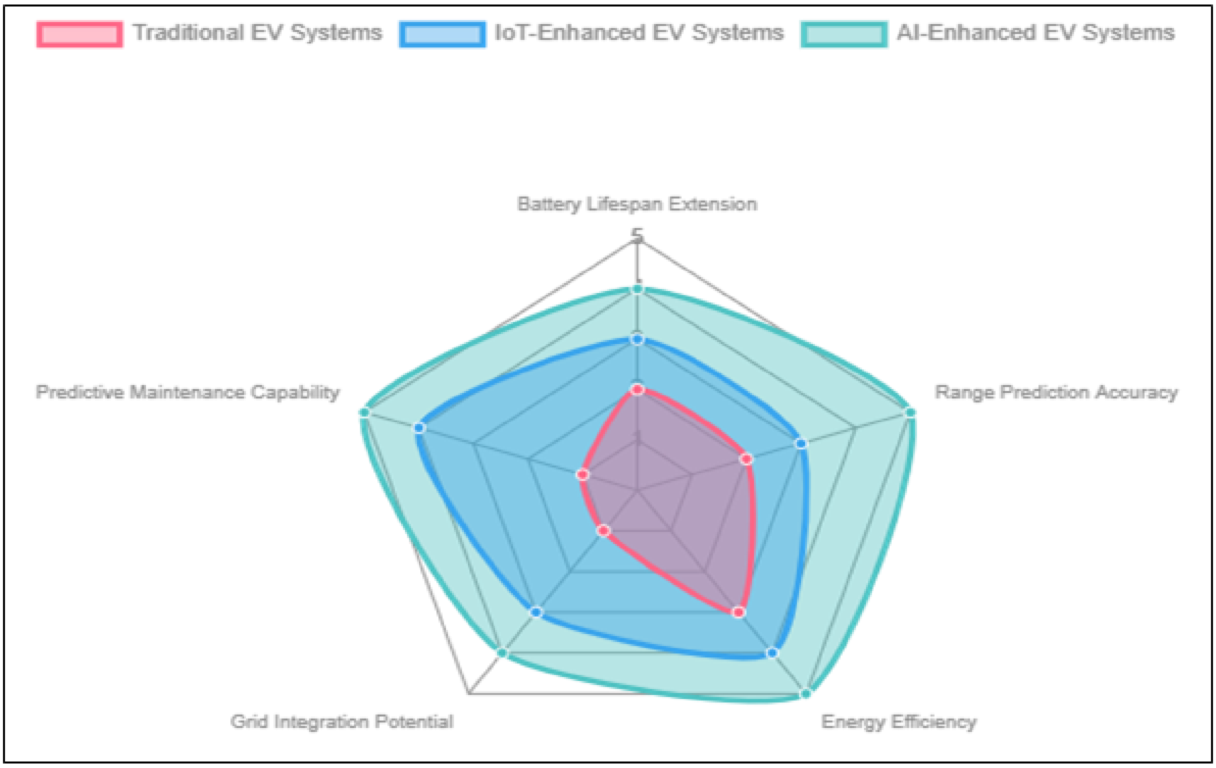

Figure II.5: Comparison of the impact of traditional, IoT-enhanced, and AI-enhanced systems.

As shown in the **??**, IoT integration primarily strengthens data connectivity, enabling real-time monitoring of vehicle and environmental parameters. This continuous data acquisition lays the foundation for AI-driven optimization, which significantly improves predictive maintenance, range estimation, and adaptive control. Together, these technologies enhance overall system intelligence, energy efficiency, and user experience.

However, despite these significant advantages, several challenges remain. The massive volume of data generated by IoT sensors introduces issues related to data security, communication latency, and cloud dependency. Moreover, AI-based algorithms, while powerful, often require large training datasets, high computational resources, and robust validation to ensure reliability under real driving conditions. Integrating both technologies within real-time EMS frameworks also raises scalability and interoperability concerns, especially when interfacing with diverse vehicle architectures and smart grid infrastructures.

Therefore, while the combination of IoT and AI offers promising advancements, its practical deployment demands careful consideration of these technical and operational constraints. Balancing intelligence, efficiency, and security will be crucial to achieving truly autonomous and sustainable EV systems.

II.5.1 The Intertwined Evolution: A Mind Map of IoT and AI in EVs

The symbiotic relationship between IoT and AI in EV energy management is complex and multidimensional. Figure II.6 provides a conceptual visualization of how these two technological domains interact to form a unified ecosystem.

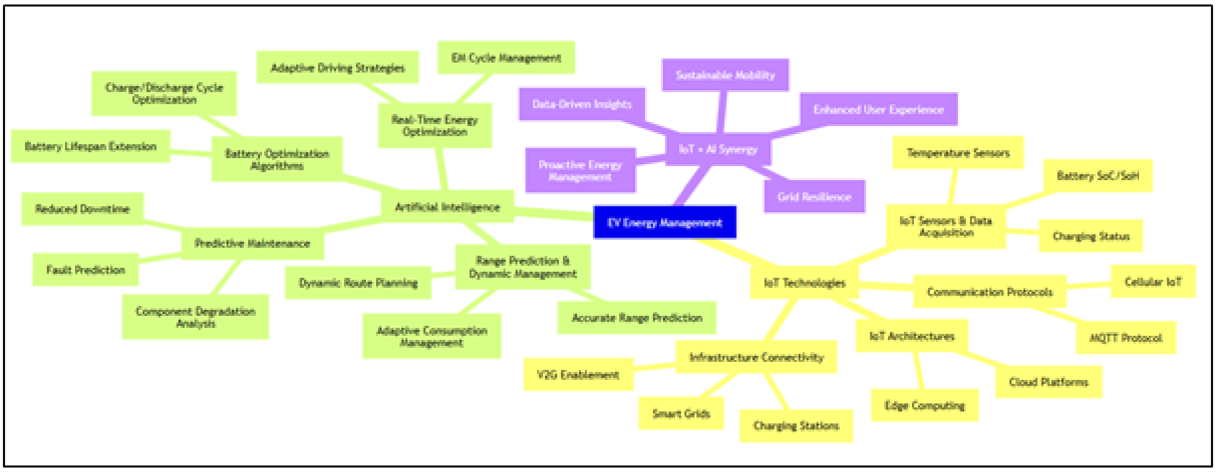

Figure II.6: Mind map illustrating the interaction between IoT and AI in EVs.

This mind map highlights the mutual reinforcement between IoT and AI componentswhere IoT ensures data acquisition and communication, and AI transforms these data into actionable insights for intelligent decision-making. Nevertheless, their combined use also requires robust architectures capable of handling cybersecurity risks, real-time constraints, and integration complexity. Understanding this intertwined evolution is essential to developing the next generation of connected, adaptive, and energy-efficient electric vehicles.

II.6 Key Contributions to EV Performance and Sustainability

The integration of IoT and AI significantly enhances various facets of EV operation, leading to improved performance, extended longevity, and greater environmental benefits [5, 14]. The table below summarizes these key contributions:

Table II.1: Key Contributions to EV Performance and Sustainability

Area of Impact	**IoT Contribution**	**AI Contribution**	**Combined Benefit**
Battery Health & Lifespan	Real-time SoC/SoH and temperature monitoring.	Optimal charge/discharge algorithms, predictive degradation.	Maximized battery health, extended operational life.
Energy Efficiency & Range	Accurate data on consumption, speed, and environment.	Adaptive driving strategies, dynamic range prediction, and route optimization.	Reduced energy waste, increased practical driving range, alleviated range anxiety.
Maintenance & Reliability	Continuous sensor data for all critical components.	Predictive fault detection, anomaly identification, and proactive scheduling.	Minimized breakdowns, lower repair costs, increased vehicle uptime.
Grid Interaction & Sustainability	Connectivity to charging stations and smart grids.	Load balancing, V2G optimization, and renewable energy integration.	Efficient energy distribution, grid stability, and reduced carbon footprint.
User Experience	Real-time information on charging availability.	Personalized charging recommendations, optimized journey planning.	Convenient and seamless charging, informed travel decisions.

This table summarizes the distinct and complementary contributions of IoT and AI to various aspects of EV energy management, highlighting the synergistic benefits that result from these collaborations.

II.6.1 Optimizing Costs and Efficiency: A Bar Chart Perspective

Beyond performance, the economic benefits of integrating IoT and AI into EV energy management are substantial. The bar chart below presents a comparative analysis of cost savings and efficiency gains across various operational aspects, illustrating the tangible impact of these technologies on operational efficiency.

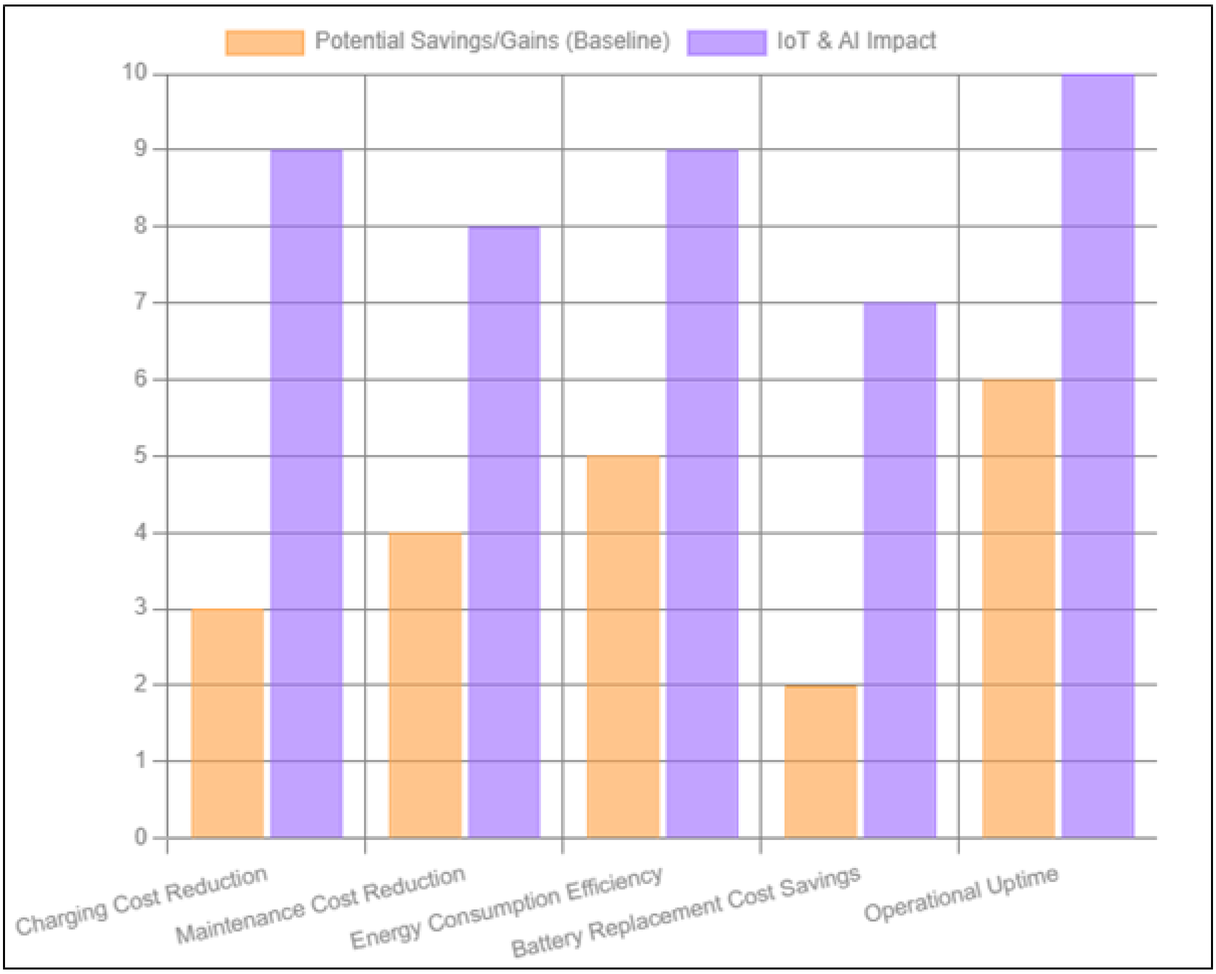

Figure II.7: Comparison of the potential for cost savings and efficiency improvements [40]

This bar chart Figure II.7 compares the potential for cost savings and efficiency improvements in various aspects of EV operation due to the integration of IoT and AI, illustrating their significant economic impact.

II.7 Conclusion

The integration of IoT and AI is evidently revolutionizing the field of electric vehicle energy management. IoT supplies vital sensing and communication functionalities, collecting comprehensive data necessary for intelligent operations. AI functions as a sophisticated analytical engine, transforming raw data into actionable insights, predictive capabilities, and real-time optimization. This collaboration enhances battery longevity, enhances range prediction accuracy, facilitates seamless integration with smart grids, and supports predictive maintenance. Consequently, this robust partnership not only elevates the performance of individual electric vehicles but also contributes to the development of a more resilient, efficient, and sustainable energy infrastructure. As these advanced technologies continue to evolve, the outlook for electric mobility appears increasingly intelligent, environmentally friendly, and interconnected.

Chapter III

Intelligent Energy Management System for Fuel Cell Electric Vehicles: Integrating Energy Storage Technologies

III.1 Introduction

The shift towards sustainable transportation is driving significant advances in electric vehicle technology, with fuel cell electric vehicles (FCEVs) gaining recognition as a promising alternative to traditional propulsion systems. By utilizing hydrogen as a clean energy carrier and incorporating efficient energy storage technologies such as batteries and supercapacitors, FCEVs seek to address limitations related to driving range, refueling time, and environmental impact. The recent development of advanced energy management systems (EMSys) enables the optimal coordination of fuel cells with auxiliary power sources, adjusting power delivery according to different operating conditions and driving profiles.

This chapter provides a detailed overview of the architectures, energy sources, and hybrid management strategies used in FCEVs. It examines the advantages and challenges of integrating fuel cells with various energy storage types, highlighting technical details, key performance metrics, and trade-offs. Through comprehensive modeling and simulation using advanced software tools, the chapter assesses how intelligent management algorithms improve system efficiency, reliability, and emissions reduction. Emphasizing hybrid configurations and real-time monitoring, it explores how these factors contribute to meeting the fluctuating power demands of modern transportation. By synthesizing current research and practical simulation results, the chapter offers insights into how integrated energy storage solutions and intelligent control strategies are shaping the future of zero-emission, adaptable electric mobility.

III.2 Fuel Cell Electric Vehicle Architectures and Hybrid Energy Management

FCEVs present a promising alternative to traditional internal combustion engine cars and battery electric vehicles, using hydrogen as a clean, high-energy-density fuel. Advances in fuel cell technology are driving their growing significance, as well as the integration of hybrid energy storage and more intelligent power management. Compared to conventional thermal systems, optimized electrical storage setupslike those described in [51] offer improved performance and system efficiency [53]. Highlight that hybrid storage not only boosts dynamic response but also increases the vehicle's range.

Despite notable progress, the large-scale deployment of FCEVs remains limited. According to [67], widespread adoption is likely only around 2030, when hydrogen production costs, storage safety, conversion efficiency, and refueling infrastructure reach mature levels.

Fuel Cell Hybrid Electric Vehicles (FC-HEVs) combine multiple energy sourcessuch as fuel cells, batteries, and supercapacitorsto meet different power needs during driving, including acceleration, deceleration, cruising, and regenerative braking. An EMSys oversees these sources, adjusting power flow in real-time. Depending on the driving situation, power may come from the fuel cell, the battery, or both. During regenerative braking, energy is recovered and stored for future use. Reference [54] shows that simultaneously charging batteries and supercapacitors greatly improves system responsiveness and energy recovery. Consequently, developing efficient EMS strategies is crucial because they impact fuel efficiency, battery lifespan, and overall driving performance.

The FCEV propulsion system includes several tightly integrated components that handle efficient energy conversion, distribution, and control, as shown in Figure III.1:

- **Fuel cell stack:** generates electrical energy from hydrogen and oxygen through an electrochemical process.
- **Hydrogen storage tank:** provides compressed hydrogen gas to the fuel cell.
- **Unidirectional DC-DC converter:** modifies the fuel cell's output to match the requirements of downstream components.
- **Bidirectional DC-DC converter:** facilitates power transfer between auxiliary storage devices (batteries, supercapacitors) and the DC bus.
- **Inverter (DC-AC converter):** transforms DC into variable-frequency AC for the electric motor.
- **Electric traction motor:** converts electrical energy into mechanical motion.
- **Drive controller:** improves vehicle performance by controlling torque and speed.

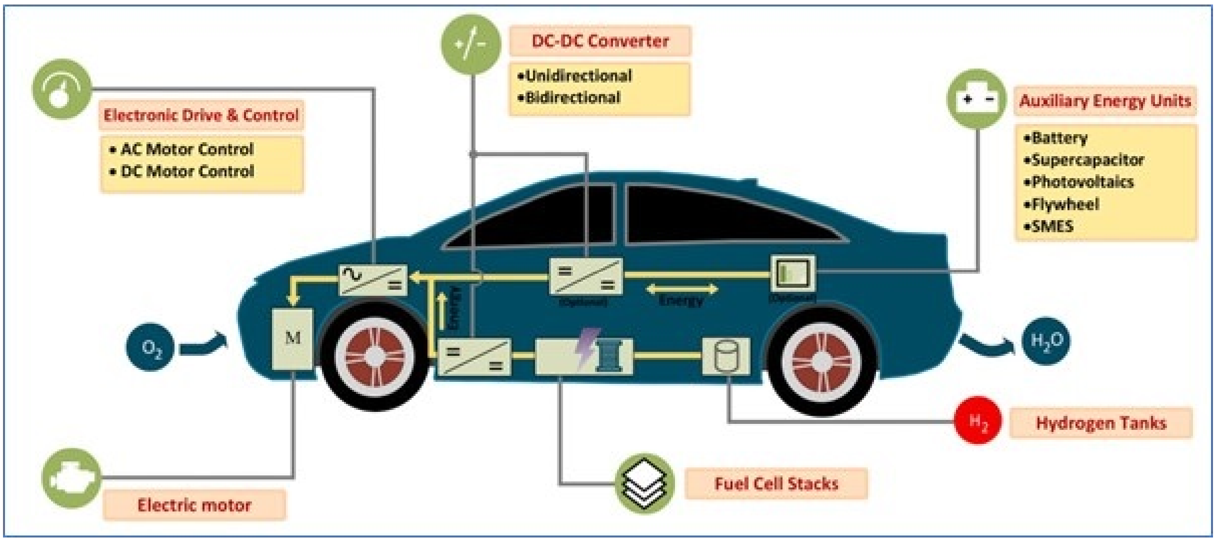

Figure III.1: Blueprint of an FCEV power transmission system with supplementary power sources [77]

References [77] and [3] outline the system architecture, featuring a Unified Electrochemical Converter (UEC) that connects directly to the fuel cell to stabilize the DC bus voltage and provide reliable power. Reference [10] highlights the inverter's function in ensuring safe and responsive motor performance across different driving scenarios.

The FCEV energy system comprises generation units such as fuel cells and photovoltaic panels, as well as storage units like batteries, ultracapacitors, flywheels, and superconducting magnetic energy storage. The choice of components depends on factors such as energy density, lifespan, power rating, recharge rate, and environmental impact.

Table III.1: Comparative overview of standard FCEV power supply technologies.

Type	**Unit**	**Energy Density (Wh/kg)**	**Life-time (Years)**	**Advantages**	**Disadvantages**
FC	Generation	Very high	20–25	Highly efficient, modular, compact, smooth output	Expensive, complex thermal and water management
PV	Generation	Medium	15–20	Clean, silent	Intermittent output, bulky for vehicles
Battery	Storage	High	4–6	Rechargeable, portable, low-cost, reliable	Slow charging, short life cycle, recycling pollution, and flammable electrolyte
UC	Storage	Very low	10–20	Rapid charging, quick response	High ownership cost
Flywheel	Storage	High	5–10	Fast charging, high power rating	Long charging time, heavy
SMES	Storage	Low	25–30	High power, short-duration storage	Very high cost

Each technology has its own strengths and limitations. Fuel cells offer high energy density and stable power, but are generally more expensive. Batteries are convenient and affordable, but their recharge speed and lifespan constrain them. Supercapacitors and SMES are well-suited for short energy bursts but face challenges related to cost and energy density.

The hybridization scheme in Figure III.2 illustrates the specific configuration used for this study. In this setup, the fuel cell is integrated with auxiliary energy storage systems, such as lithium-ion batteries, lead-acid batteries, and supercapacitors, to meet the vehicle's dynamic power demands effectively. As shown in the figure, this integrated energy management forms the foundation of the hybrid configuration selected for the simulation in this work. The design aims to capitalize on the advantages of each energy source, thereby improving energy efficiency, responsiveness, and overall system reliability across various operating conditions.

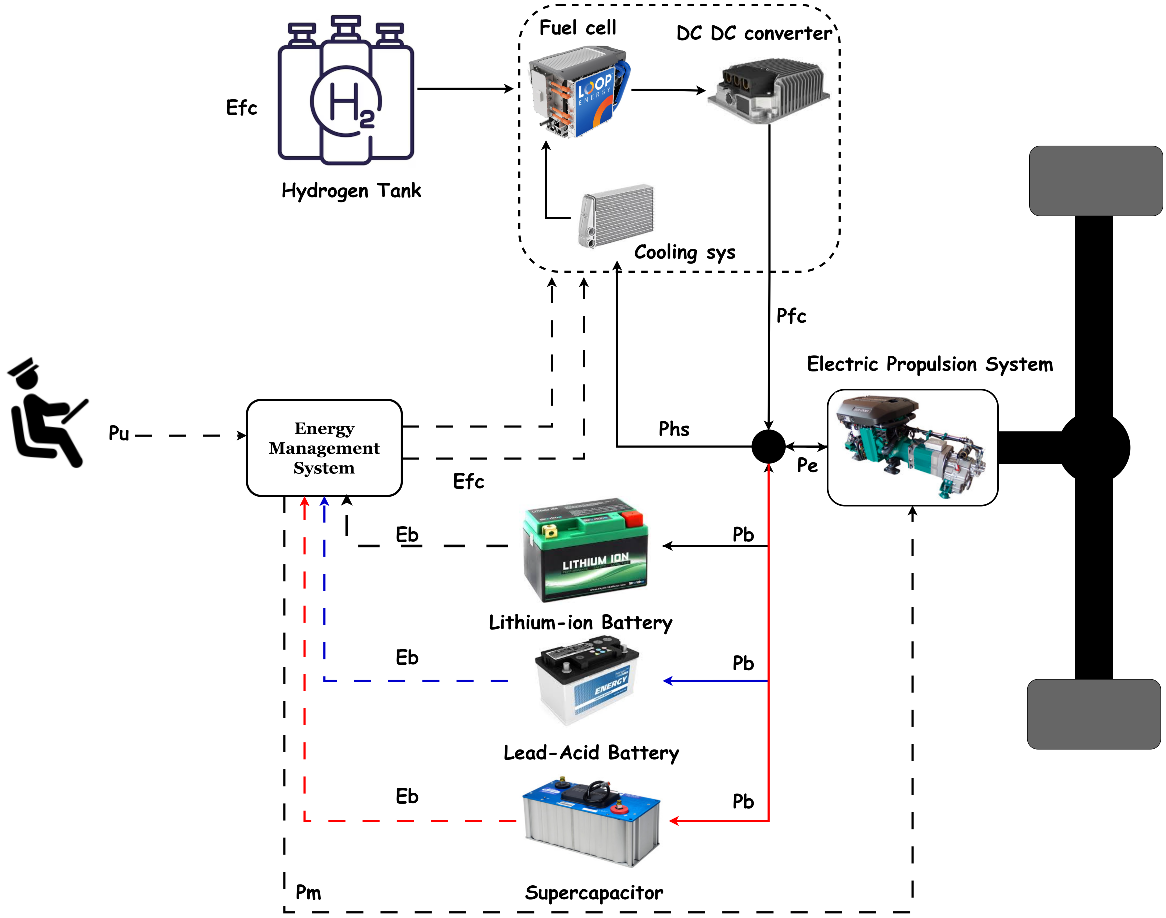

Figure III.2: Fuel Cell Electric Vehicle Energy Hybridization.

III.3 Energy sources

Electric vehicles get power from different energy sources for their motors and auxiliary systems, mainly using batteries, supercapacitors, and fuel cells. Each option has its own advantages and disadvantages related to energy density, power, lifespan, cost, safety, and environmental impact. These factors are essential when designing EV systems.

Batteries remain the most common energy source in EVs because of their high energy density and mature technology. Lithium-ion batteries are especially common because of their ample storage capacity and longer driving range. However, batteries have a limited lifespan due to chemical breakdown from repeated charging and discharging. Issues like high costs, recycling challenges, and safety risks, including thermal runaway, continue to raise concerns.

Supercapacitors have less energy storage capacity than batteries but excel at delivering or absorbing quick, high-power bursts. This makes them useful during vehicle acceleration, start-up, or regenerative braking. They are known for their durability and safety. However, because of their lower energy density, they are most effective as a supplement to the central battery system rather than a standalone power source.

Fuel cells transform the chemical energy of hydrogen into electricity, offering advantages such as a longer range and quicker refueling compared to batteries. However, they encounter challenges including higher costs, integration difficulties, safety issues related to hydrogen, and the requirement for specialized hydrogen infrastructure.

To balance the advantages of various sources, hybrid systems combining batteries with supercapacitorsor batteries with fuel cellsare increasingly utilized in advanced electric vehicle designs. Recent research has advanced energy management solutions, such as [8], which have developed systems to coordinate the operation of batteries and supercapacitors for improved efficiency and longer device life. [15] created real-time control strategies for hybrid storage setups that include batteries, fuel cells, supercapacitors, and superconductors. Additionally, [22] investigated hybridization with renewable sources to enhance variable management within storage systems, as discussed in [61], and presented a multi-battery configuration to optimize fuel cell electric vehicles.

Choosing the best energy setup ultimately depends on the specific application, the needed level of hybridization, and the trade-offs between energy density, peak power, lifespan, cost, and ecological impact. The wide range of energy storage options and continuous advancements in innovative management strategies are enabling EVs to achieve higher efficiency and greater flexibility, better meeting market needs and sustainability objectives.

III.3.1 Fuel Cell technology

Fuel cells (FCs) are electrochemical devices that convert fuelprimarily hydrogeninto electricity through redox reactions, offering an efficient way to generate both electrical power and heat [45]. A fuel cell stack consists of multiple electrochemical cells connected in series to produce the voltage needed for vehicle operation. This research emphasizes Proton Exchange Membrane Fuel Cells (PEMFCs), which are commonly used in EVs because of their low operating temperatures (20-100 °C) and quick start-up times. They rely on a polymer membrane as an electrolyte to facilitate hydrogen oxidation at the anode and oxygen reduction at the cathode. Figure III.3 displays the core structure, including the anode, electrolyte, and cathode.

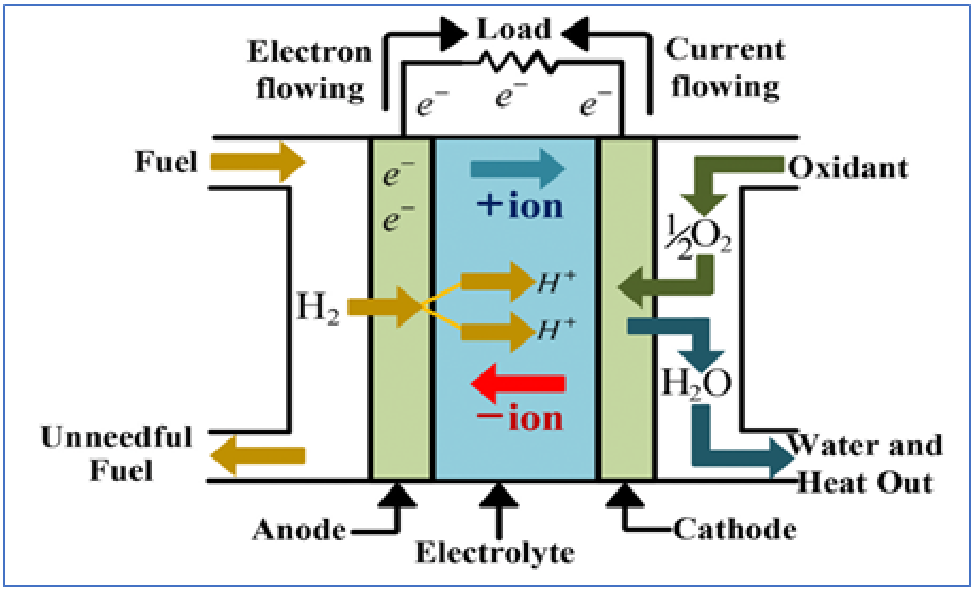

Figure III.3: Essential operation of an FC.

In operation, hydrogen at the anode splits into protons and electrons. The protons move through the membrane to the cathode, while the electrons are directed via an external circuit to generate electricity. At the cathode, oxygen reacts with the protons and electrons to create water, releasing heat [76]. The involved electrochemical reactions are as follows:

$$2\,H_2 + 2\,e^- + \frac{1}{2}\,O_2 \longrightarrow H_2O \quad \text{(Cathode)} \tag{III.1}$$

$$H_2 \longrightarrow 2\,H^+ + 2\,e^- \quad \text{(Anode)} \tag{III.2}$$

$$H_2 + \frac{1}{2}\,O_2 \longrightarrow 2\,H_2O \quad \text{(Net: Heat + Electrical Energy)} \tag{III.3}$$

Fuel cell performance is affected by various types of losses: activation, ohmic, and concentration losses. Activation losses, mainly from the cathodic reaction, are described by the Tafel equation [35]:

$$V_{\text{act}} = A\,k\,\ln\left(\frac{I_{\text{FC}} + I_n}{I_0}\right) \tag{III.4}$$

where I_{FC} is the current delivered by the fuel cell, I_0 is the exchange current characterizing the electrode-electrolyte exchanges in the off-load state, I_n is the internal current allowing for possible crossing of gas and/or electrons through the electrolyte, and k is the slope of the Tafel line.

Ohmic losses are due to the resistance of the bipolar plates opposing the circulation of electrons and the electrolytes passage of protons. The corresponding voltage drop is:

$$V_{\text{ohm}} = R_m(I_{\text{FC}} + I_n) \tag{III.5}$$

where R_m represents the total resistance of the fuel cell.

Concentration losses V_{conc} are given by:

$$V_{\text{conc}} = -B \ln \left(1 - \frac{I_{\text{FC}} + I_n}{I_L}\right) \tag{III.6}$$

where B is a mass transfer constant and I_L is the limiting current.

Finally, the voltage of a fuel cell can be expressed statically as:

$$V_{\text{cell}} = V_{\text{therm}} - \eta_{\text{act}} - R_m I_{\text{FC}} - \eta_{\text{con}} \tag{III.7}$$

where V_{therm} is the theoretical potential (as a function of temperature and pressure), η_{act} represents activation losses, and $R_m I_{\text{FC}}$ accounts for ohmic losses mainly due to the membrane.

The primary sources of ohmic overvoltage, η_{okm}, is attributed to the transport of protons in the membrane, given by:

$$\eta_{okm} = R_m \cdot i \tag{III.8}$$

with i the local current density and R_m is the membrane resistance.

Hence, the expression for the electrical resistance of Nafion, according to Homs' law [26] is given by:

$$R_{ohm} = \frac{l_m}{\sigma_m(a)} \tag{III.9}$$

where σ_m is the membrane conductivity [S/m] and H_{ml} is the membrane thickness [m].

The fuel cell output voltage is given by:

$$V_{FC} = E_{nerst} - V_{act} - V_{con} - V_{ohm} \tag{III.10}$$

where V_{FC} is the voltage of a cell, E_{nerst} is the thermodynamic potential, V_{act} is the activation losses, V_{con} is the concentration loss and V_{ohm} Ohmic losses due to internal resistance.

A fuel cell consists of several cells placed in series to form an array, with a voltage given by:

$$V_{stack} = N \cdot V_{FC} \tag{III.11}$$

where N is the number of cells in series, V_{stack} is the stack's output voltage.

However, the power of the fuel cell is the product of the voltage and the current, given by the following equation:

$$P_{power} = V_{stack} \times I_{FC} \tag{III.12}$$

where V_{stack} is the array voltage and I_{FC} is the cell current. A detailed electrochemical model capturing the static behavior of fuel cells is presented by [4]. The electrical analogy of a fuel cell can be represented through an equivalent circuit, as shown in Figure III.4

Theoretically, the reaction between oxygen and hydrogen produces a voltage of 1.23 V, but in practice, this value is usually lower. Normally, a FC offers about 0.6 to 0,7 V at nominal load.

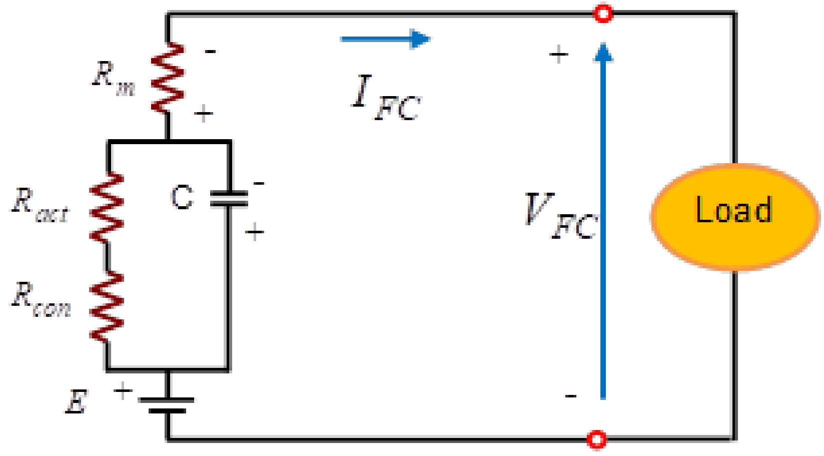

Figure III.4: Equivalent electrical diagram of a Fuel Cell.

During operation, factors like activation loss, ohmic resistance, and mass transfer limitations lead to a decrease in voltage while the current increases.

Fuel cells are categorized by their chemical makeup and operating temperatures, as summarized in Table 2. The main types include DMFC, SOFC, AFC, MCFC, PAFC, and PEMFC.

Fuel cells are used in distributed generation, portable power, backup power, military, space, and automotive sectors. Among these, low-temperature and pressure fuel cells are most common in automotive use because they offer high power density, operate at lower temperatures (60 to 80 °C), and have less corrosion.

III.3.2 Batteries for Electric Vehicles

Batteries play a crucial role in EVs, converting chemical energy into electrical energy that powers the traction motor and onboard systems. Besides providing propulsion, they also store regenerative braking energy and manage high-power transients caused by varying driving conditions. The three main types of rechargeable batteries used in EVs are lead-acid, nickel-metal hydride , and lithium-ion. Among these, lithium-ion and lead-acid batteries are the most favored for hybrid systems with fuel cells, thanks to their higher energy density, longer durability, and extended driving range, as summarized in Table III.3.

Battery capacity is an essential measure of performance, indicating the energy storage (in ampere-hours, Ah) a battery can hold under optimal conditionsconstant current and temperature. However, this capacity decreases as the discharge rate rises, which can be represented mathematically as:

$$C_{bat} = \int_{t_i}^{t_f} i \, dt \tag{III.13}$$

where i is the battery discharge current [A], t_i and t_f are the battery start and end states.

To size the battery stack to increase its lifespan and ensure system autonomy, the following

Table III.2: Comparison of different types of fuel cells and their main characteristics

Types	PEMFC	PAFC	AFC	SOFC	MCFC	DMFC
Stack power (kW)	< 1-250	50-100	1100	< 1-3000	300-3000	0.001-100
Cell Voltage (V)	1.1	1.1	1.0	0.8-1.0	0.7-1.0	0.2-0.4
Operating temperature (řC)	< 100	150-200	90-100	500-1000	600-700	60-200
Efficiency (%)	40-60	40	60	60	50	40
Advantages	Low operating temperature, fast start-up, compact design, and low corrosion rate.	Moderate temperature operation, good fuel impurity tolerance, suitable for CHP systems.	High efficiency, low material cost, rapid start-up, and fast electrochemical kinetics.	High efficiency, fuel flexibility (H_2, CO, CH_4), and CHP/hybrid capability.	High efficiency, fuel flexibility, suitable for large-scale stationary applications.	Compact design, direct methanol use, low system cost, and simple operation.
Disadvantages	High catalyst cost (Pt-based), hydrogen purity sensitivity, and limited durability.	High cost, slow start-up, and degradation under CO poisoning.	Sensitive to CO_2 in air and fuel streams, complex water management, and limited durability.	High operating temperature, material degradation, and long start-up time.	Corrosion issues, high temperature, and long start-up duration.	Low efficiency, slow kinetics, methanol crossover, and short lifespan.

formula determines the nominal capacity of the battery pack:

$$C_b = \frac{E_b \times Aut}{V_{bn} \times D_b} \quad \text{(III.14)}$$

With C_b as the nominal capacity of the pack [Ah], E_b is the daily energy to be stored in the pack [Wh/d], Aut is the number of days of autonomy, V_{bn} the nominal voltage of the pack [V], and D_b the depth of discharge of the pack in [%].

To analyze the voltage and state of charge responses of the batteries, in states of charge/dis-

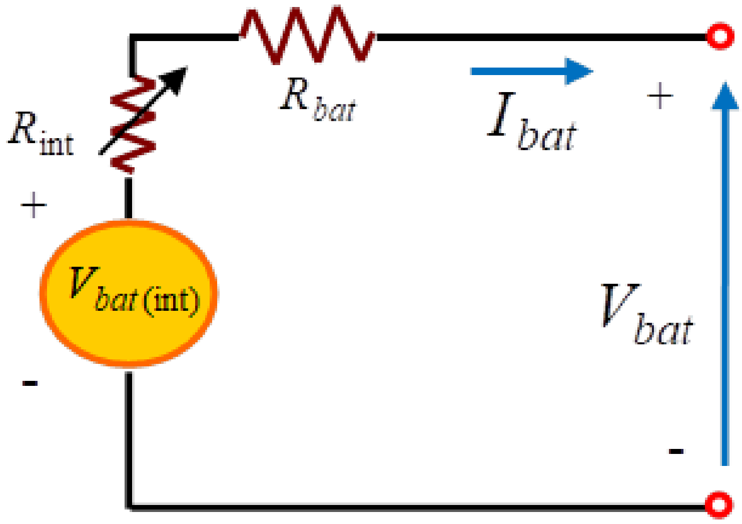

Figure III.5: Equivalent electrical diagram of a battery.

charge at a constant current, the number of batteries in series and in parallel is:

$$\begin{cases} N_s = \frac{V_n}{V_{n1}} \\ N_p = \frac{C_n}{C_{n1}} \\ N_{bat-tot} = N_s \times N_p \end{cases}$$

where N_s is number of batteries in series, N_p number in parallel, $N_{bat-tot}$ total number, V_n nominal voltage of the batteries, V_{n1} nominal voltage of one battery, C_n nominal capacity of the batteries, C_{n1} for a single battery.

The specific energy of a battery (Wh/kg) is:

$$P = \frac{V^2}{4(R_{ohm} + R_{int})_{max}} \tag{III.15}$$

where R_{ohm} is ohmic resistance and R_{int} internal resistance.

The power-to-weight ratio refers to the maximum power output of the battery in relation to its weight. The internal resistance greatly influences this ratio.

Battery voltage consists of an internal voltage source with an associated ohmic resistance and internal resistance, resulting from a chemical reaction. This represents the voltage drop, which is related to the battery current, determined by:

$$V_{bat} = V_{bat(int)} - (R_{ohm} + R_{int})I \tag{III.16}$$

where $V_{bat(int)}$ is the internal battery voltage.

Therefore, the vehicle's range depends on the battery's energy, which is a function of its voltage V_{bat} and capacity C_{bat}, as:

$$E_{bat} = V_{bat} \times C_{bat} \tag{III.17}$$

The SoC indicator is defined as the ratio of remaining capacity to maximum capacity when fully charged, varying between SoC_{min} and SoC_{max}.

Hence, the change in SoC over an interval dt, with discharge or charge current i_{bat}:

$$\begin{cases} \Delta SoC = \frac{i\,dt}{C_{bat}} \\ SoC(t) = SoC(0) - \int \frac{i_{bat}}{C_{bat}} dt \end{cases}$$

where C_{bat} is the ampere-hour capacity of the battery, i_{bat} is current (positive for discharge, negative for charge).

Also, the ratio between its actual capacity at a given aging state and nominal capacity is:

$$SoH(\%) = \frac{\text{Maximal capacity in current aging state}}{\text{Nominal capacity}} \times 100 \tag{III.18}$$

Battery performance and energy consumption are greatly affected by real-world conditions such as vehicle load, terrain, wind speed, and especially driving cycle (urban stop-and-go vs highway). To accommodate these factors, energy management algorithms regulate charging and discharging based on expected load and speed. Proper battery sizing, advanced monitoring, and innovative energy control strategies enable EV systems to balance performance, battery life, and energy independence.

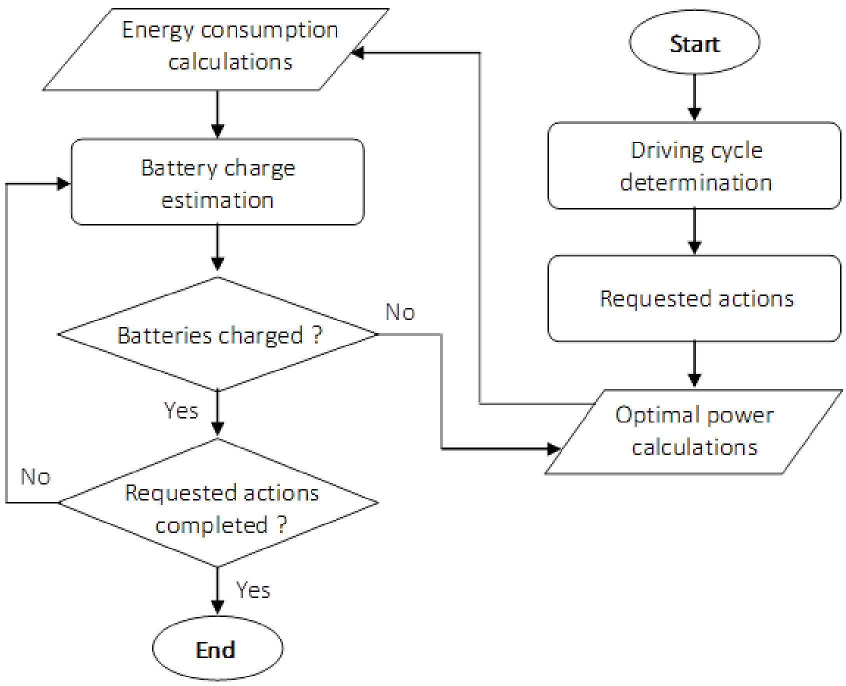

Figure III.6: Relationship between battery charge and requested actions.

III.3.2.1 Lead-acid batteries

One of the earliest and most popular rechargeable battery technologies available on the market is lead-acid. Because of their inexpensive starting cost, great energy efficiency (over 80%), quick reaction, and low self-discharge rate of around 2% per month at 25 °C, they are often used in home backup systems, car starters, and uninterruptible power supply. Their moderate specific energy density of 30 to 50 Wh/kg and normal cycle life of 1,500 cycles, however, are their limitations. Furthermore, there are health and environmental issues with the growing usage of lead-acid batteries, particularly in relation to lead poisoning and the dangers of inappropriate disposal.

III.3.2.2 Batteries based on nickel

Nickel-iron, nickel-cadmium (NiCd), nickel-metal hydride (NiMH), and nickel-zinc (NiZn) are among the chemistries used in nickel-based batteries. They use an alkaline potassium hydroxide electrolyte, sometimes with lithium hydroxide additions, and nickel hydroxide as the positive electrode. Depending on the chemistry, the negative electrode may be zinc hydroxide in NiZn, cadmium hydroxide in NiCd, or a metal alloy in NiMH. Lead-acid batteries are surpassed by nickel-based batteries, which have specific energy densities between 50 and 95 Wh/kg. With a cycle life of up to 10,000 cycles, NiCd batteries are very robust, which makes them perfect for applications requiring resilience and endurance under circumstances of deep drain. However, due to the toxicity of cadmium, some variationsparticularly NiCdare now being closely monitored by regulators.

III.3.2.3 Batteries made of lithium

Modern energy storage is based on lithium-ion batteries (LiBs), particularly in electric cars and high-tech products. They have a significant energy density (up to 250 Wh/kg), remarkable specific power (up to 4,000 W/kg), and high specific energy (90-190 Wh/kg). LiBs are a more ecologically responsible choice since they don't have memory effect and don't contain dangerous heavy metals like lead, mercury, or cadmium. In order to attain the necessary capacity and voltage for certain applications, especially in electric cars, lithium-ion battery packs usually include numerous electrochemical cells integrated into modules. Their high initial cost is their main obstacle, which may prevent them from being adopted in areas where prices are sensitive.

Table III.3: Comparison of Different Battery Types

Battery Type	Specific Power (W/kg)	Specific Energy (Wh/kg)	Life (Years)	Cycle	Efficiency (%)	Cost ($/kWh)
Lead-acid battery	50–180	30–50	3–15	500–4500	70–90	50–200
Ni-based battery	50–1000	30–70	15–20	100–40,000	50–90	150–2400
Li-based battery	250–400	90–190	∼15	500–18,000	80–95	100–2000

Although lead-acid batteries are easy to use and reasonably priced, their lifetime and energy capacity are limited. Although they are more expensive, nickel-based batteries provide an excellent mix between modest performance and longevity. Although they are more expensive, lithium-ion batteries provide the greatest performance. The best battery option will rely on your price, lifespan, and power requirements. Performance of electric cars, such as driving range, acceleration, and thermal management, is greatly impacted by the balance between power consumption and battery load. Because of heat stress and deep discharge cycles, higher loads might cause wear more quickly, which could shorten lifetime. Regenerative braking, variable power distribution, and sophisticated thermal regulation are examples of energy management techniques that are essential for reducing battery stress. By maximizing energy transmission, minimizing power spikes, and significantly extending battery life, these strategies improve vehicle economy. Cost, longevity, environmental effect, and energy and power needs must all be taken into account when choosing a battery technology. Lead-acid batteries are more affordable for low-demand uses, whereas nickel-based and lithium-ion batteries are better suited for long-term, high-performance applications. Despite their greater cost, lithium-ion batteries are particularly preferred in grid storage and next-generation electric cars due to their superior energy density and dependability. To satisfy the changing requirements of electrified systems, ongoing advancements in battery chemistry and energy management are crucial.

III.3.3 Supercapacitors for Electrified Vehicles

The characteristics of rechargeable batteries and conventional capacitors are combined in a unique energy storage device called a supercapacitor. It offers the energy storage capacity of batteries as well as the rapid charging and high-current discharge capabilities of capacitors. Based on how they function, supercapacitors are primarily classified as electric double-layer capacitors (EDLCs) or pseudocapacitors [44].

In today's world, energy and electrical supply systems' dependability, security, and quality are becoming more and more crucial. Microgrids are a new kind of electrical infrastructure that uses distributed power production to meet these demands. In this regard, supercapacitors provide a novel and exciting energy storage option that may improve the overall energy quality of microgrids by offering both short-term power and energy buffering. Consequently, one of the most popular energy storage technologies in microgrid systems nowadays is supercapacitors [74]. Their various applications are shown in Figure III.7.

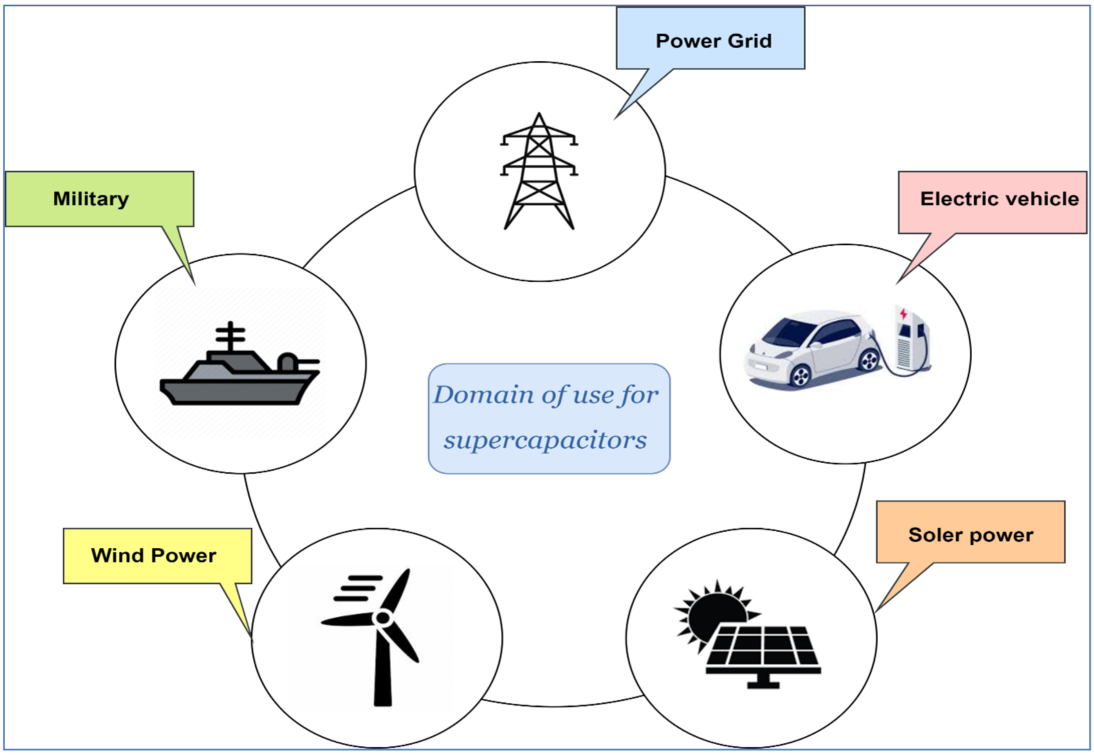

Figure III.7: Supercapacitors' field of application.

Supercapacitors are energy storage devices that are ideal for use in electric and hybrid cars because of their quick release of electrical energy. They provide functions including regenerative braking, short-term storage, and burst-mode energy delivery. The materials used for the electrodes and electrolytes of a supercapacitor define its specific kind.

A simplified representation of a supercapacitor is an RC circuit, as shown in Figure III.8, where R_{sc}, R, represents the equivalent series resistance (reflecting Joule losses), and C represents the capacitance. C_{sc} denotes the primary capacitance.

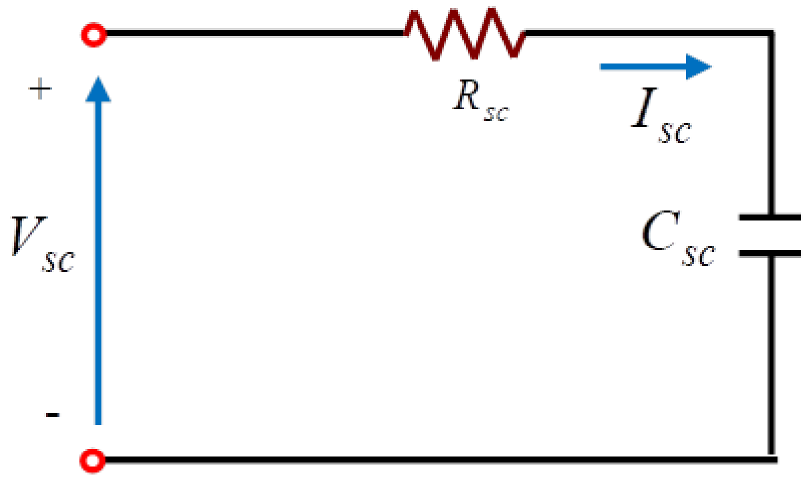

Figure III.8: Equivalent electrical diagram of a supercapacitor.

The series resistance R_{sc} is obtained from the voltage drop at the beginning of a charging or discharging process under a constant current and is expressed as:

$$R_{sc} = \frac{V_{sc}}{I_{sc}} \tag{III.19}$$

where R_{sc} is the series resistance of a supercapacitor cell, V_{sc} is the voltage across the cell terminals and I_{sc} is the current flowing through the supercapacitor.

The voltage across a supercapacitor is given by:

$$V_{sc} = E_{sc} - R_{sc} \cdot I_{sc} \tag{III.20}$$

with E_{sc} the energy stored in the supercapacitor cell.

The capacitance of a supercapacitor cell C_{sc} is determined directly from the response characteristic following a constant-current discharge of the cell, given by:

$$C_{sc} = \frac{I_{sc} \cdot t_{dis}}{\Delta V} \tag{III.21}$$

Impedance spectrometry can be used to determine the differential capacitance of the supercapacitor, which is written in the following form:

$$C_{diff} = C_0 + K_x \cdot V_t \tag{III.22}$$

The charge current flowing through the differential capacitance of the supercapacitor as a function of the time derivative of the voltage is given by:

$$I_{sc} = C_{diff}(V_t) \times \frac{dV_t}{dt} \tag{III.23}$$

The relationship between the total charge across the supercapacitor and the current is given by:

$$Q_{tot} = \int I_{sc} dt = \int C_{diff}(V_t)\, dV_t \tag{III.24}$$

Combining equations (27) and (28), the total charge will be given by:

$$Q_{tot} = \int (C_0 + K_x V_t)\, dV_t = (C_0 + \frac{K_x}{2} V_t) \cdot V_t \tag{III.25}$$

where Q_{tot} is the total charge across the supercapacitor, K_x is the impedance spectrometry parameter, and V_t is the supercapacitor voltage as a function of time.

Thus, the total charge capacity of the cell is calculated for a zero voltage reference, as follows:

$$C_{tot} = C_0 + \frac{K_x}{2} V_t \tag{III.26}$$

The current I_{sc} is positive during the discharge state and negative during the charge state, with the power applied to this circuit given by:

$$P_{sc} = V_c \cdot I_{sc} \tag{III.27}$$

with $P_{sc} > 0$ in the discharge or traction state and $P_{sc} < 0$ in the charge or braking state.

Supercapacitors help extend battery life by supporting high-power demands and rapid charge-discharge cycles. The major types of supercapacitors include:

III.3.3.1 Electric Double-Layer Capacitors

Electric Double-Layer Capacitors (EDLCs) depend on forming electrical double layers (EDLs) at the electrode-electrolyte interface. Their capacitance varies with voltage-dependent charge storage. As shown in Figure III.9, EDLCs typically use activated carbon with a high surface area as the electrode and operate with either aqueous or organic electrolytes. They generally provide capacitances from a few farads and function at voltages of a few volts. Due to their high-power density and long cycle life, EDLCs are the most prevalent type of supercapacitor.

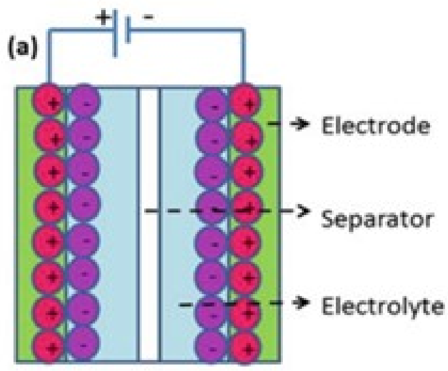

Figure III.9: EDLC structure

III.3.3.2 Pseudocapacitors

As seen in Figure III.10, pseudocapacitors store charge by faradaic processes such intercalation, redox reactions, and electrosorption. In comparison to EDLCs, these mechanisms provide better specific capacitance and energy density. Metal oxides and conductive polymers are common electrode materials. Because of limitations imposed by solvent breakdown and electrochemical stability, pseudocapacitors usually operate at lower voltages, even though they may produce capacitances many times larger than that of EDLCs.

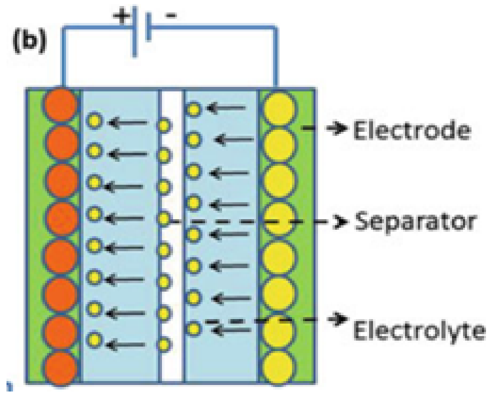

Figure III.10: Pseudocapacitor structure

III.3.3.3 Hybrid Capacitors

The characteristics of EDLCs and pseudocapacitors are combined in hybrid supercapacitors. These devices usually have two electrodes, one that is identical to an EDLC electrode and the other that is pseudocapacitive, like a battery, as shown in Figure III.11. A wider range of voltages is made possible by this configuration's better energy and power densities. Because of their different electrode materials, some people call them "asymmetric" supercapacitors. Their capacitance, which sometimes reaches several hundred farads per gram, normally lies between that of EDLCs and pseudocapacitors.

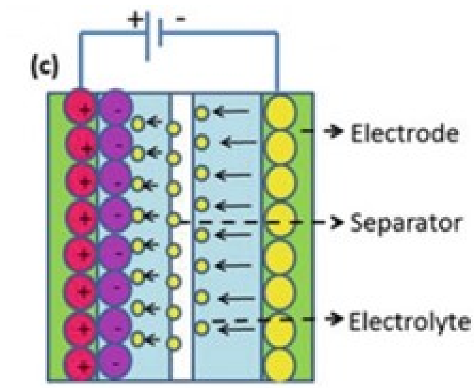

Figure III.11: Hybrid Capacitor structure

Supercapacitors are gaining popularity due to their ability to deliver high power quickly and their long lifespan. To help choose the right type for specific uses, Table III.4 provides a comparison of different supercapacitor benefits, and drawbacks. This overview is designed to aid informed choices when designing and integrating energy storage solutions in various engineering fields.

Table III.4: Advantages and Disadvantages of Different Types of Supercapacitors

Type	**Advantages**	**Disadvantages**
Electric Double-Layer Capacitors (EDLCs)	At high voltages and power levels, carbon is the preferred material for electrodes.	An electrochemical double layer is formed through a non-Faradaic process that stores charge.
Pseudocapacitors	Conducting polymers and metal oxides are used as electrode materials. Both redox and Faradaic reactions can store charge.	Solvent decomposition voltage and electrochemical limits restrict low-voltage operation.
Hybrid Capacitors	Composed of materials combining carbon with metal oxides or conductive polymers. Capable of higher cell voltage.	The charge is stored through both Faradaic and non-Faradaic processes.

III.4 Analysis of Energy Storage in Fuel Cell Electric Vehicles with ADVISOR Software

A detailed examination of energy storage in FCEVs is essential for improving their efficiency, range, and overall performance. This study emphasizes the use of ADVISOR software, a flexible simulation tool, to assess various energy storage and management strategies for FCEVs. By offering realistic insights into component interactions, ADVISOR enables researchers and engineers to optimize design decisions that impact vehicle autonomy, efficiency, and sustainability.

The Advanced Vehicle Simulator (ADVISOR) was created in the late 1990s by the National Renewable Energy Laboratory (NREL) primarily to analyze hybrid vehicle systems through simulation. Its main strength is supporting both forward and backward simulations, enabling engineers to simulate actual drive cycles and evaluate the energy performance of entire powertrains. Since its debut, ADVISOR has been extensively used in academic research, automotive industry projects, and commercial applications [24, 73]. Over the years, various user-submitted models and component datasets have been added to its library, broadening its capabilities to include diverse energy storage setups and fuel cell types.

ADVISOR is an open-source tool capable of analyzing various systems, including dynamic, instantaneous, linear, non-linear, and hybrid types. Its adaptability makes it particularly valuable for examining interactions between energy sources during real-world driving. It features a graphical interface and advanced computational tools to visualize torque distribution, wheel behavior, velocity, and energy flows. This enables ADVISOR to simulate and clearly illustrate the link between power demand profiles and the roles of different energy sources. Additionally, it allows researchers to compare different powertrain designs across standardized driving cycles, ensuring consistent testing conditions for various configurations [68].

The software offers users a collection of predefined driving cycles, making it easy to create customized scenarios. Its drag-and-drop components and modular interface allow researchers to set up FCEV configurations, simulate energy storage behavior, and assess performance trade-offs. For instance, the system can model hybrid fuel cellbattery systems to find the most efficient energy management strategies. NREL has worked closely with academic partners and major automakers to calibrate these models, ensuring high accuracy and reducing uncertainties in the simulation results.

When launching ADVISOR, the initial interface guides the user to configure the essential parameters, as shown in Figure III.12, before executing the vehicle simulation. After setup, the tool delivers detailed results on fuel consumption, battery charge/discharge patterns, system efficiency, and emissions, providing a solid foundation for performance optimization research in FCEVs.

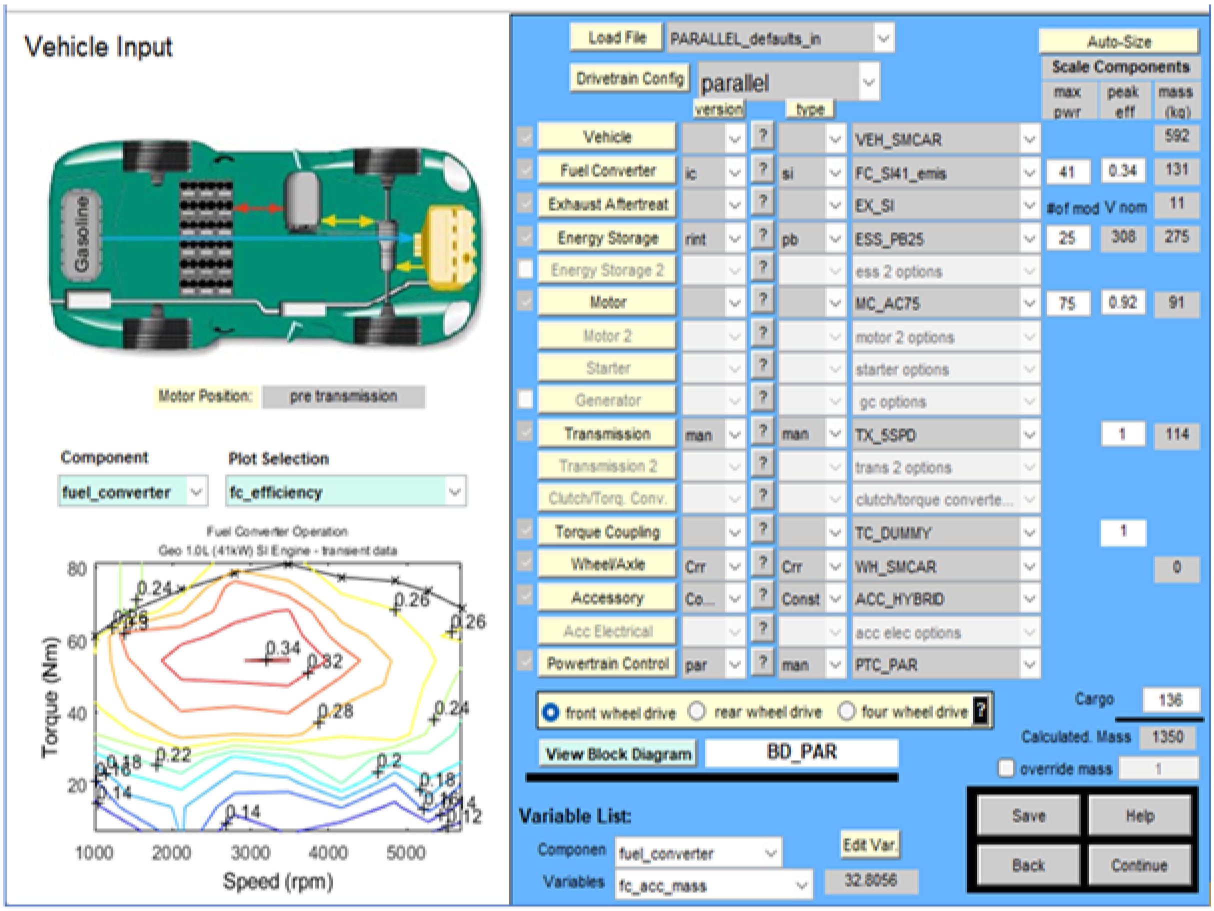

Figure III.12: ADVISOR interface

III.4.1 Modeling of FCEV in ADVISOR

This research uses the ADVISOR simulation platform to model fuel cell electric vehicles (FCEVs) and compare various hybridization topologies. This comparison enables an evaluation of how various powertrain architectures impact efficiency, energy consumption, and driving performance.

A systematic analysis of these configurations offers valuable insights into the optimal strategies for energy distribution and storage in FCEVs.

ADVISOR is highly suitable for this type of investigation because of its intuitive graphical interface and modular simulation environment. The software features three main screens, each crafted to facilitate a seamless modeling workflow. These screens guide users through vehicle definition, simulation running, and performance analysis in a clear and structured manner. This design enables the exploration of various FCEV configurations without requiring advanced programming knowledge, making it accessible to both researchers and engineers.

The study's systematic methodology involves several key steps. First, a baseline FCEV model is chosen from the ADVISOR component library. Then, various hybridization architectures are introduced, enabling comparisons among designs such as pure fuel cell systems, fuel cellbattery hybrids, and fuel cell-ultracapacitor setups. After establishing the technical parameterssuch as power ratings, energy storage capacities, and control strategiesthe models undergo testing on standardized drive cycles. The resulting data include metrics such as energy efficiency, fluctuations in battery state of charge, fuel consumption, and emission profiles, providing a comprehensive overview of performance.

Modeling FCEVs in ADVISOR offers a detailed view of their dynamic performance, operational features, and efficiency in real-world driving conditions. This method enhances understanding of sustainable powertrain options and facilitates the advancement of next-generation FCEV technologies. As shown in Figure III.13, the ADVISOR interface visually displays the components and energy flows in FCEV modeling, making it a valuable tool for simulation and educational use.

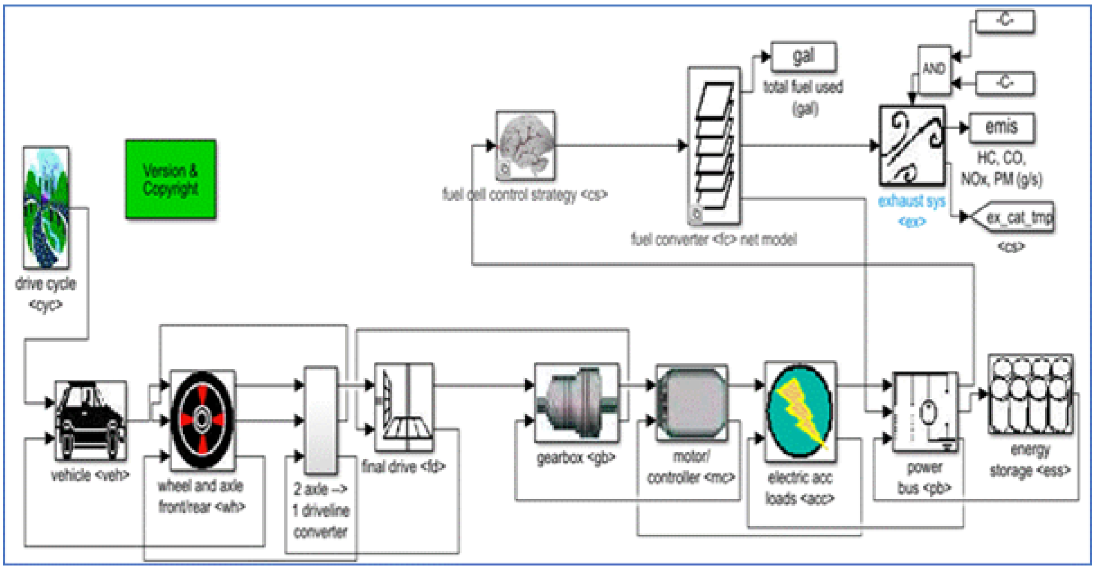

Figure III.13: Modeling of FCEV in ADVISOR.

The powertrain of a fuel cell electric vehicle (FCEV) is essential to its performance and efficiency. Figure III.14 illustrates the main powertrain components of a fuel-cell electric vehicle.

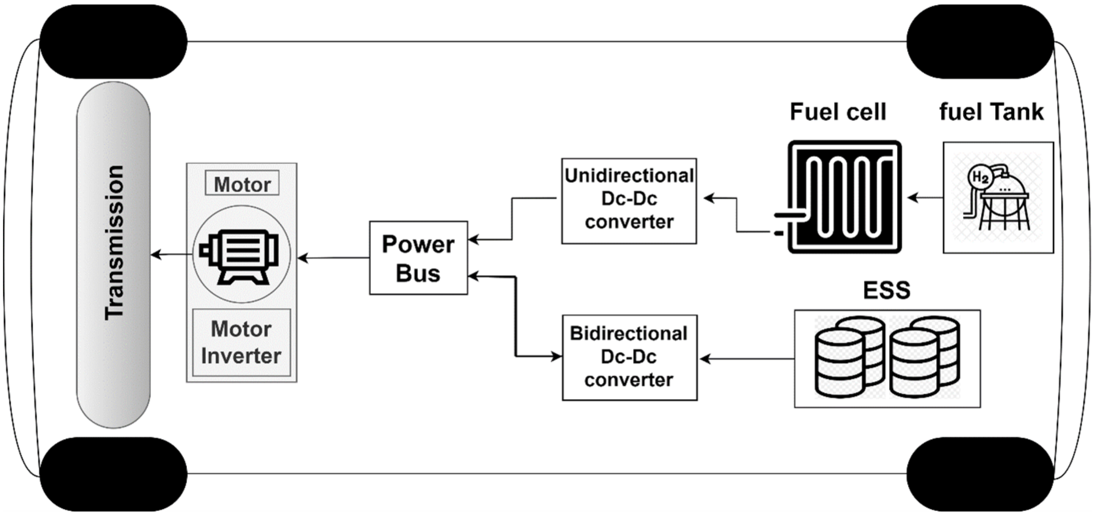

Figure III.14: Powertrain FCEV

- **Transmission:** The transmission transmits power from the engine to the vehicle's wheels.
- **Motor:** The electric motor converts electrical energy into mechanical motion.
- **Motor Inverter:** The motor inverter controls the power supplied to the motor.
- **Power Bus:** The power bus connects all powertrain components.
- **DC-DC converters** manage the voltage between the vehicle's various systems.
- **Fuel Cell:** The fuel cell generates electricity from hydrogen.
- **Fuel Tank:** The hydrogen tank stores fuel.
- **ESS:** The energy storage system stores excess electricity.

FCEVs are a practical choice for eco-friendly transportation because of their drivetrain, which allows them to run effectively and cleanly on hydrogen fuel. When building an automobile, parts must be carefully chosen to guarantee both technical correctness and operation. Using the FCEV Parameters listed in Table III.5, a comprehensive analysis of the chosen FCEV was carried out. These materials provide a thorough grasp of the hydrogen fuel cell vehicle's potential and capabilities by providing in-depth details regarding its performance, technical specs, and salient characteristics. Table III.5 lists important vehicle attributes, including engine, propulsion type, mass, frontal surface area, fuel storage system, and energy storage system. These specifics are essential for modeling and simulating vehicle performance, assessing energy consumption, range, and dynamic behavior, and improving overall vehicle operation in both fuel-powered and electric models.

Table III.5: Vehicle and Energy Source Parameters

Category	Parameter	Value
Vehicle	Vehicle mass (kg)	1380
	Frontal Area (m^2)	2
	Type of vehicle (wheel)	Front Wheel
	Aerodynamic drag coefficient	0.335
	Wheel Radius (m)	0.282
	Accessory power (W)	700
	Motor mass (kg)	91
	Coefficient of rolling drag	0.009
	Motor max power (kW)	75
Fuel Cell	FC max power (kW)	50
	FC peak efficiency	60%
	FC mass (kg)	223
Lead-acid Battery	Lead-acid Battery max module number	25
	Lead-acid Battery maximum Voltage (V)	308
	Lead-acid Battery initial SoC	70%
	Lead-acid Battery mass (kg)	275
Lithium-ion Battery	Lithium-ion Battery max module number	25
	Lithium-ion Battery maximum Voltage (V)	267
	Lithium-ion Battery initial SoC	70%
	Lithium-ion Battery mass (kg)	28
Supercapacitor	Supercapacitor max module number	25
	Supercapacitor maximum Voltage (V)	44
	Supercapacitor initial SoC	70%
	Supercapacitor mass (kg)	10

III.5 Investigation results

The proposed energy management strategy for a FCHV was thoroughly tested across three standardized driving cycles: the Urban Dynamometer Driving Schedule (UDDS), US06, and CYC_CBD14. These cycles were chosen because they cover a range of real-world driving conditions and operational challenges. Using these test scenarios, the analysis provides a detailed evaluation of how different hybrid energy storage configurations perform in urban settings, high-load situations, and congested stop-and-go traffic.

Each cycle offers distinct insights into how the fuel cell system interacts with the auxiliary energy storage. Visualizing vehicle speed trajectories during drive cycles reveals variations in power demand. Additionally, simulations using ADVISOR provide detailed data on energy consumption, transient load sharing, and the evolution of SoC across various storage configurations.

Together, this method facilitates both a qualitative understanding of power demand trends and a quantitative assessment of energy efficiency.

III.5.1 Obtained results for the first UDDS driving cycle

The UDDS driving cycle, the first scenario, represents normal urban driving with a lot of stops and starts as well as mild accelerations. Three hybrid configurations were used to examine the fuel cell vehicle's energy performance in this scenario: a fuel cell coupled with a lead-acid battery, a lithium-ion battery, and a supercapacitor.

The UDDS cycle has varying vehicle speeds with many peaks and troughs that reflect traffic situations in cities, as seen in Figure III.15. The hybrid energy management system's power requirements fluctuate due to these speed variations, necessitating efficient coordination between the fuel cell and storage energy sources.

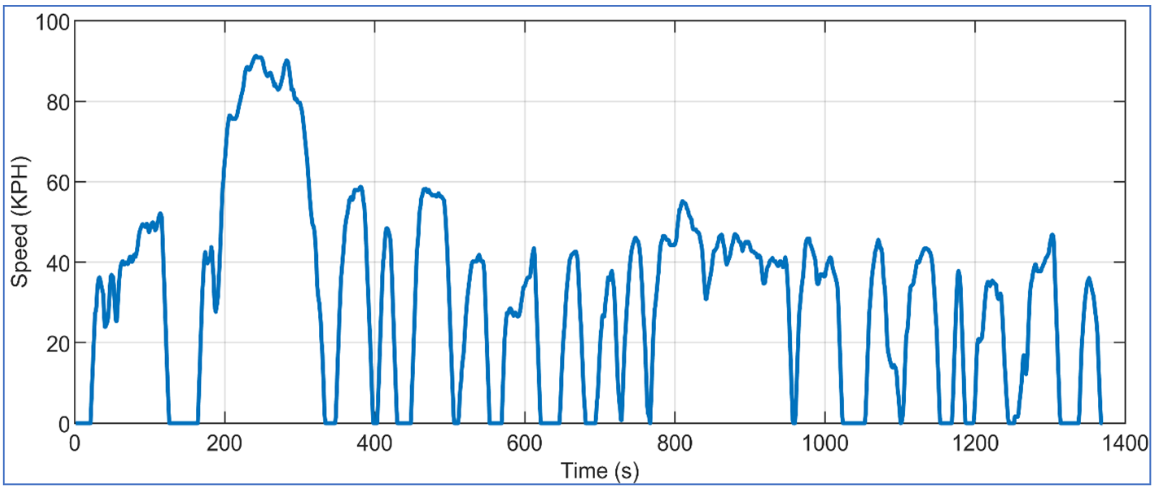

Figure III.15: Drive cycle UDDS.

III.5.1.1 Hybridization: Fuel Cell + Lithium-Ion Battery

The power distribution between the lithium battery and the fuel cell is shown in Figure III.16. Between 0 and 20,000 W, the fuel cell (green curve) supplies a constant base power that makes up around 60% of the vehicle's overall demand. With a maximum capacity of 30,000 W, the lithium-ion battery (red curve) offers assistance during periods of high-power consumption. Additionally, with a recovery efficiency of up to 80%, it collects regenerative braking energy during deceleration (down to -5,000 W).

The SoC trend is shown in Figure III.17, which shows cyclic charging and discharging within a 20% range. This demonstrates effective battery utilization without putting the system under stress. Importantly, the battery provides or absorbs the required energy within the first 200 seconds to compensate for the fuel cell's delayed reaction.

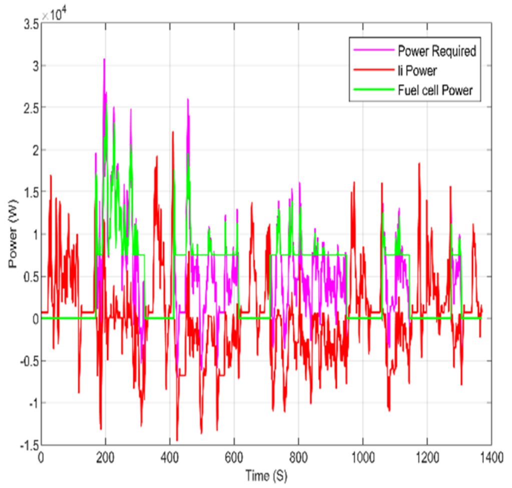

Figure III.16: Power of a Lithium battery.

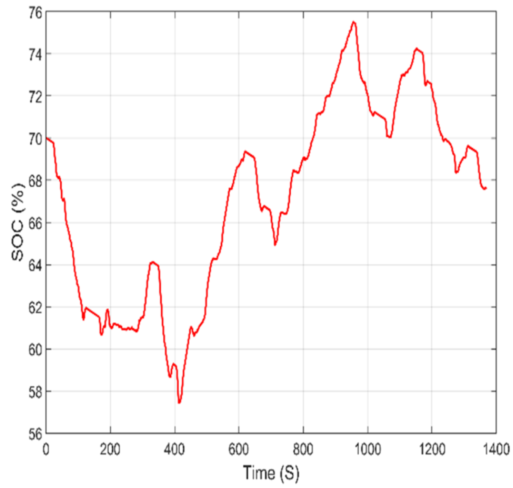

Figure III.17: SoC of a Lithium battery.

III.5.1.2 Hybridization: Fuel Cell + Supercapacitor

Figure III.18 and Figure III.19 demonstrate that the supercapacitor provides minimal energy, contributing less than 5% of the total energy during the UDDS cycle. While some charging occurs, it does not discharge enough to meet peak loads. This is because the UDDS cycle's low fluctuation in power demand is not enough to activate the high-power, short-duration features of supercapacitors.

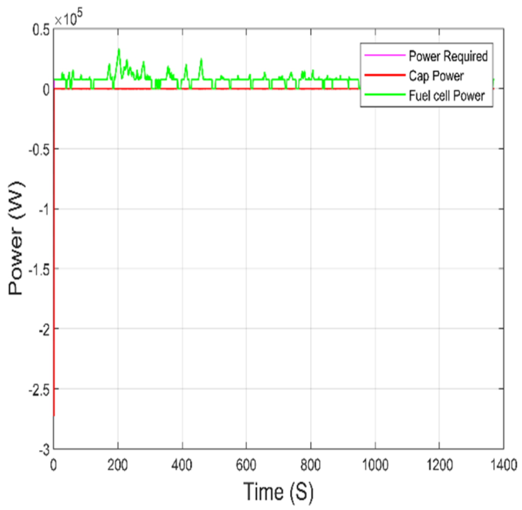

Figure III.18: Power of Supercapacitor.

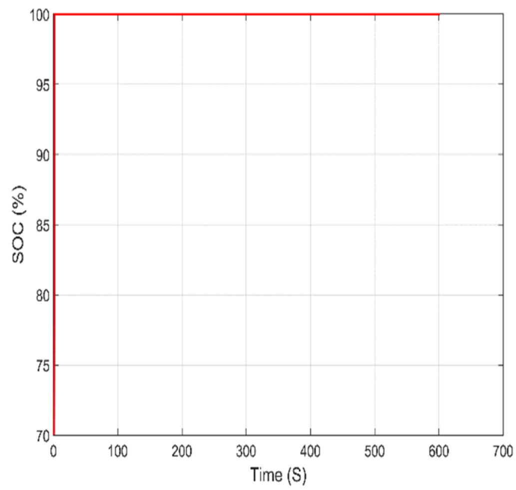

Figure III.19: SoC of Supercapacitor

III.5.1.3 Hybridization: Fuel Cell + Lead-Acid Battery

Figure III.20 and Figure III.21 demonstrate that the lead-acid battery provides support at peak demands, although to a lesser extent than the lithium battery. The fuel cell reliably functions, diminishing to a minimum of 8,000 W during times of low demand. The battery undergoes repeated charge and discharge cycles, with the state of charge varying by around 15%. Its responsiveness is somewhat diminished owing to elevated internal resistance and reduced charge uptake relative to lithium-ion batteries.

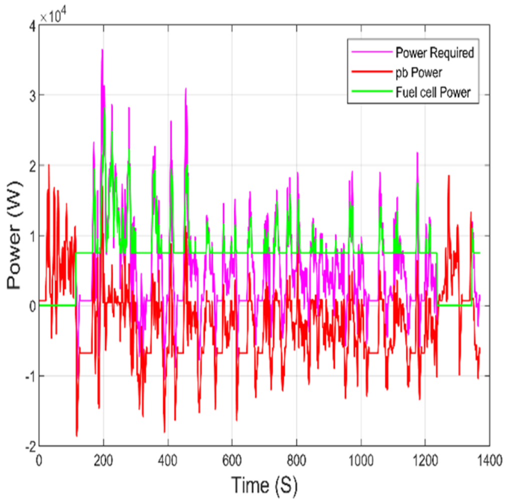

Figure III.20: Power of a Lead-Acid Battery.

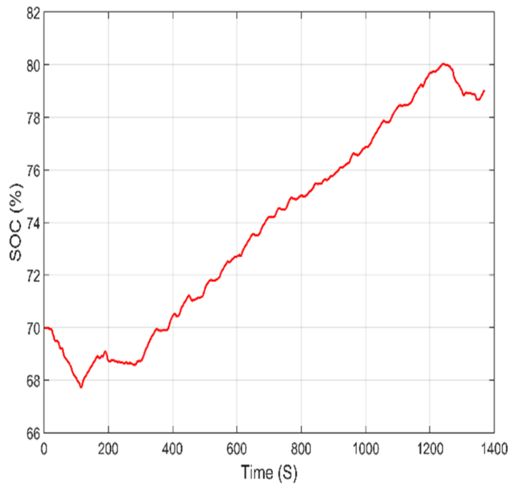

Figure III.21: SoC of Lead-acid battery.

III.5.2 Results for the US06 Driving Cycle

The second cycle tested is US06, which mimics aggressive, high-speed driving involving quick accelerations and decelerations. As shown in Figure III.22, it features speeds over 130 km/h and simulates challenging real-world scenarios. This cycle assesses the effectiveness of energy management strategies in responding to increased power demands.

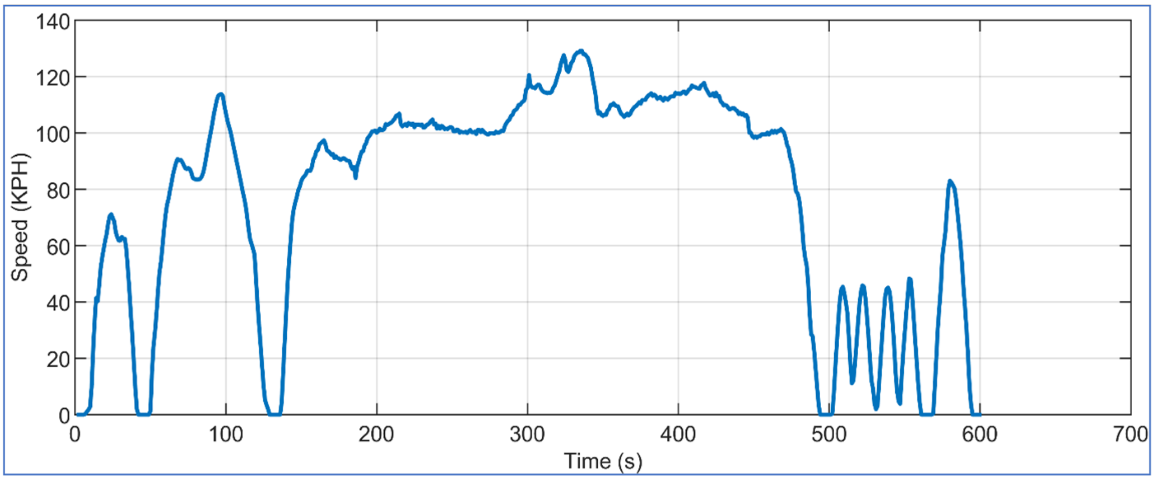

Figure III.22: Drive cycle US06.

III.5.2.1 Hybridization: Fuel Cell + Lithium-Ion Battery

Figure III.23 shows that the lithium-ion battery's contribution becomes significantly more substantial than in the UDDS scenario, accounting for up to 50% of the peak power demand. The fuel cell coordination guarantees a steady power supply during rapid acceleration and high-speed cruising. The SoC evolution (see Figure III.24) indicates more intense cycling than in the UDDS case, reflecting the higher power exchange and energy flow.

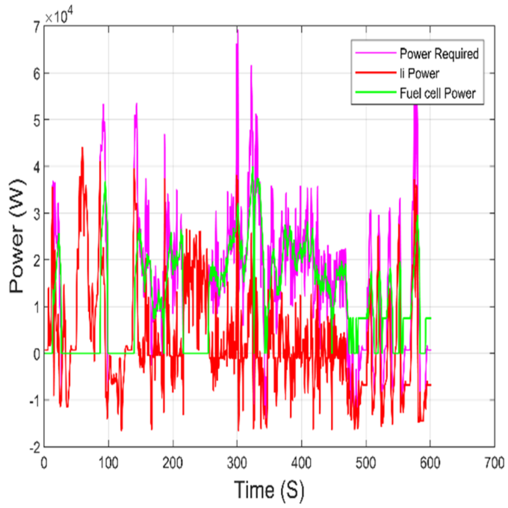

Figure III.23: Power of a Lithium battery.

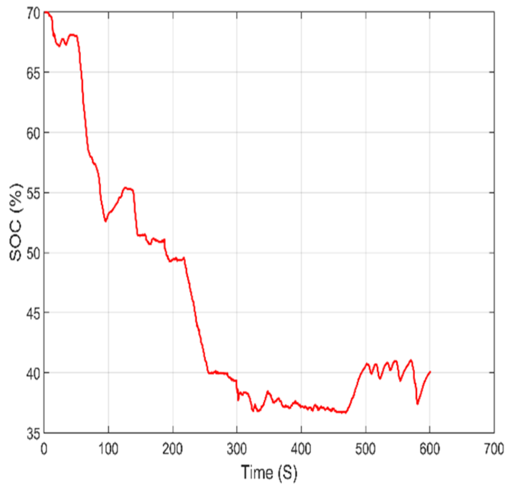

Figure III.24: SoC of a Lithium battery.

B2. Hybridization: Fuel Cell + Supercapacitor Despite the US06 cycle's more aggressive profile, the supercapacitor's contribution remains minimal (under 8% of total energy), as illustrated in Figure III.25 and Figure III.26 Although it undergoes a broader SoC variation (10%), its energy storage potential remains underutilized, likely because extended power demands are more suitable for battery systems.

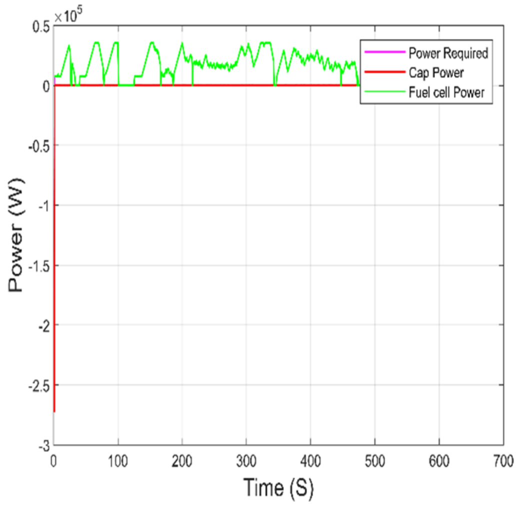

Figure III.25: Power of Supercapacitor.

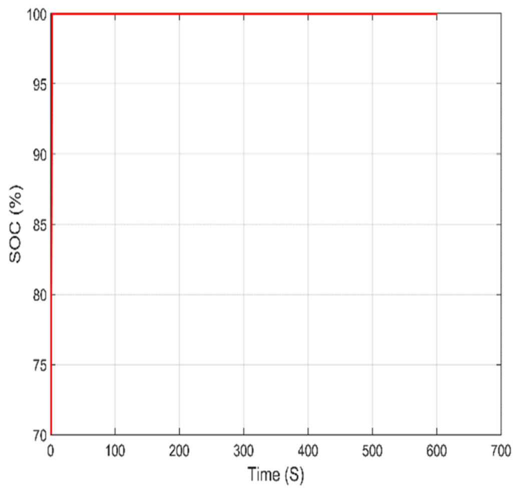

Figure III.26: SoC of Supercapacitor.

III.5.2.2 Hybridization: Fuel Cell + Lead-Acid Battery

Figure III.27 and Figure III.28 (assuming State of Charge) demonstrate that the lead-acid battery exhibits comparable performance under US06 circumstances, but with somewhat reduced efficiency and responsiveness. The lead-acid system supplies about 30% of the power peaks, supplemented by a continually functioning fuel cell.

Energy usage in the US06 cycle escalated by around 25% relative to the UDDS, attributed to heightened demand, leading to more intensive battery use. Both lithium-ion and lead-acid batteries efficiently assisted the fuel cell in meeting energy requirements, with an energy recovery efficiency of up to 70%.

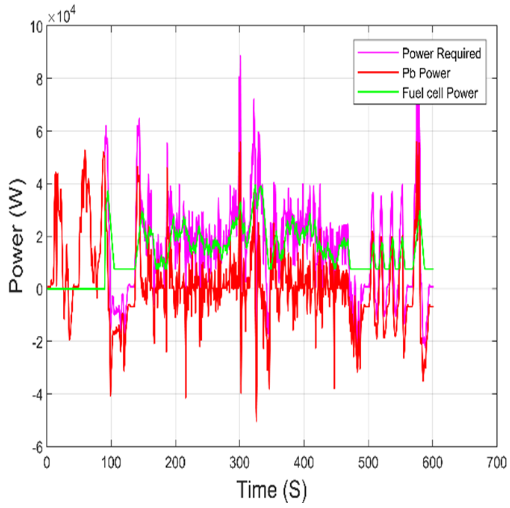

Figure III.27: Power of a Lead-Acid Battery.

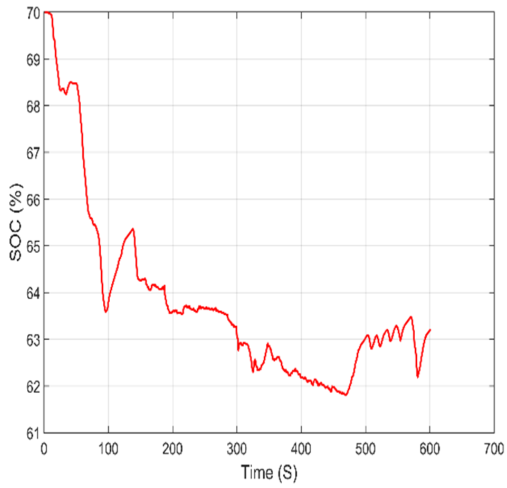

Figure III.28: SoC of a Lead-Acid Battery.

III.5.3 Results for the CYC_CBD14 Driving Cycle

The CYC_CBD14 profile (Figure III.29) models dense urban center traffic, characterized by brief accelerations followed by rapid stops. It presents the most complex scenario for energy recovery and transient load management.

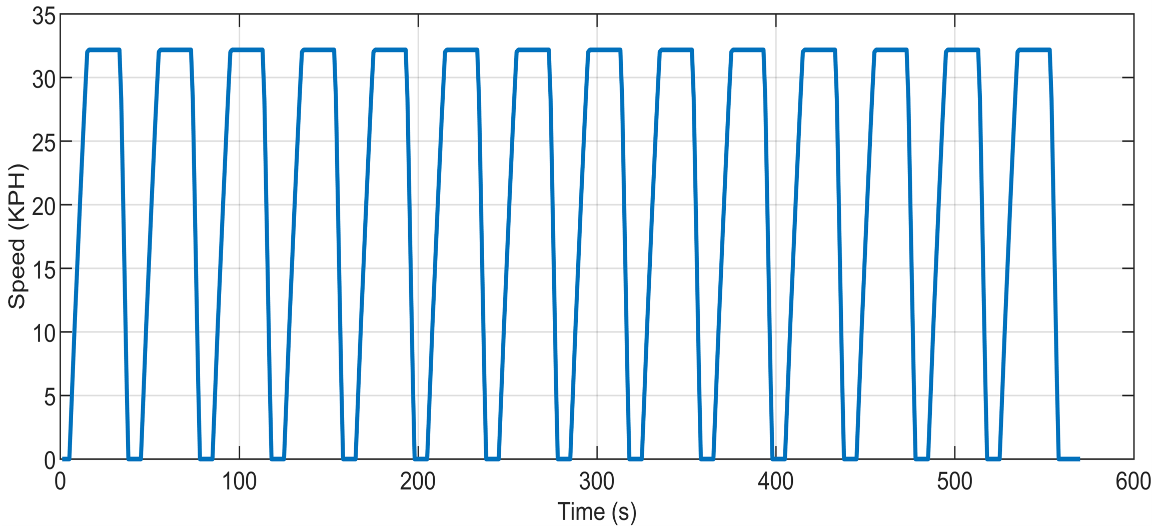

Figure III.29: Drive cycle CYC_CBD14.

III.5.3.1 Fuel Cell + Lithium Battery

The lithium battery (Figure III.30) manages 70% of transient loads, maintaining vehicle responsiveness during frequent stops and starts. The SoC (Figure III.31) demonstrates effective energy regeneration, reaching a peak of 69%. Meanwhile, the fuel cell provides a consistent 55% of the total power, thereby improving overall system endurance.

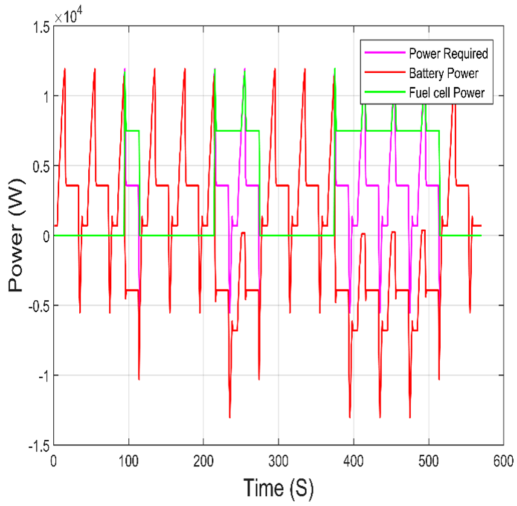

Figure III.30: Power of a Lithium battery

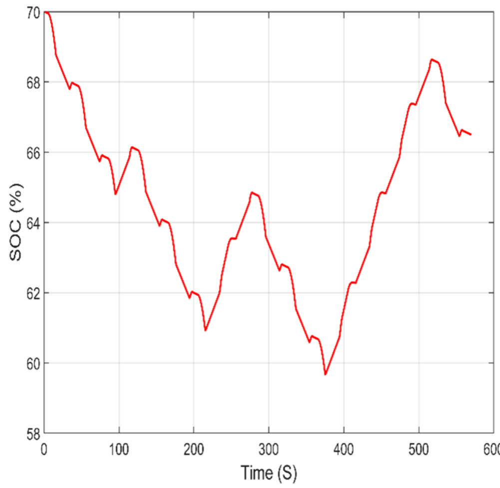

Figure III.31: SoC of a Lithium battery

III.5.3.2 Fuel Cell + Supercapacitor

Figure III.32 and Figure III.33 continue to show low engagement. Despite a 12% change in SoC, the supercapacitor does not significantly contribute to the energy supply. The control strategy seems to prefer fuel cell-lithium or fuel cell-lead-acid combinations in these low-speed scenarios.

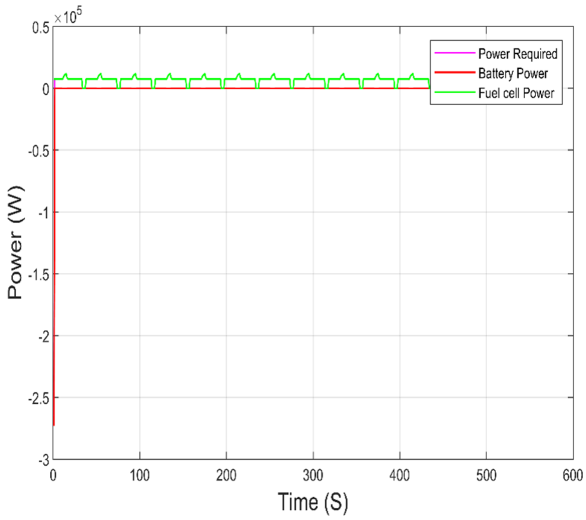

Figure III.32: Power of Supercapacitor.

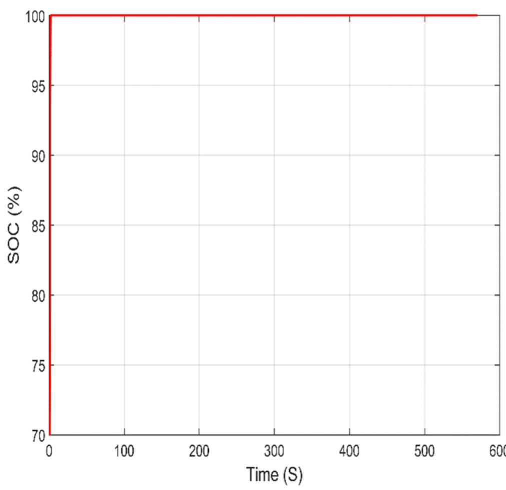

Figure III.33: SoC of Supercapacitor.

III.5.3.3 Fuel Cell + Lead-Acid Battery

The lead-acid battery (Figure III.34) only supplies power for the first 100 seconds, demonstrating its ability to fulfill urgent energy requirements prior to the fuel cell's activation. The State of Charge (Figure III.35) diminishes by 10% prior to the engagement of the fuel cell. This early independence illustrates effective short-term buffering, yielding about a 12% increase in energy efficiency relative to single-source systems.

Across all driving cycles, the use of lithium batteries in hybrid systems reliably enhances energy recovery and responsiveness while decreasing the load on the fuel cell. Lead-acid batteries provide sufficient albeit less dynamic performance, particularly during initiation. In contrast, supercapacitors exhibit suboptimal performance owing to their low efficiency and restricted energy output under all testing circumstances.

The energy management system adeptly adapts to varying driving circumstances, enhancing the fuel cell's efficiency and facilitating substantial energy recovery. Future initiatives should concentrate on improving control systems for supercapacitor applications and broadening hybridization testing to evaluate long-term endurance and temperature constraints.

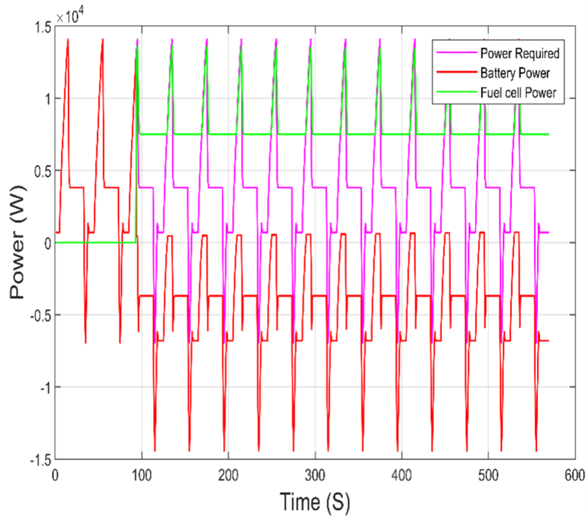

Figure III.34: Power of a Lead-Acid Battery.

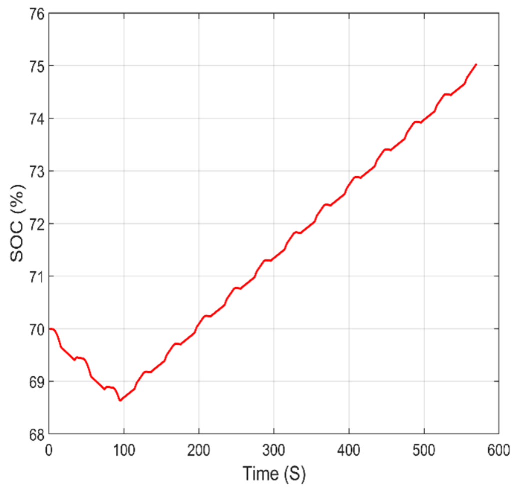

Figure III.35: SoC of a Lead-Acid Battery.

III.5.4 Efficiency of Fuel Cell Vehicle with hybrid configurations

The findings highlight the need of using diverse energy sources to adequately address the variable energy requirements while driving. This approach significantly enhances system performance. Combining fuel cells (FC) with lithium-ion batteries, supercapacitors, and lead-acid batteries may improve efficiency by around 15% to 20%, depending on driving circumstances. Figure III.36 to Figure III.44 demonstrate the fuel cell efficiency in different hybrid configurations during three driving cycles: UDDS, US06, and CYC_CBD14, as shown in Figure III.15, Figure III.22, and Figure III.29, respectively. In all instances, the fuel cell sustains an efficiency of 50% to 60%, aligning with its ideal operational range. The fuel cell mostly functions during high energy demand times, supplying almost 70% of the total energy at peak loads, as verified by the efficiency study.

III.5.4.1 FC + Lithium Battery Configuration

In the first hybridization scenario with a lithium-ion battery:
For the UDDS cycle (Figure III.36), the fuel cell vehicle exhibits an efficiency ranging from 48% to 55%, with the power output varying between 7 and 25 kW.
For the US06 cycle (Figure III.37), efficiency improves slightly, ranging from 48% to 58%, with the power output increasing to between 7 and 40 kW, addressing the higher dynamic requirements of this aggressive driving cycle.
For the CYC_CBD14 urban cycle (Figure III.38), efficiency remains between 49% and 55%, corresponding to a power demand of 8 to 12 kW, which is typical of congested urban driving conditions.

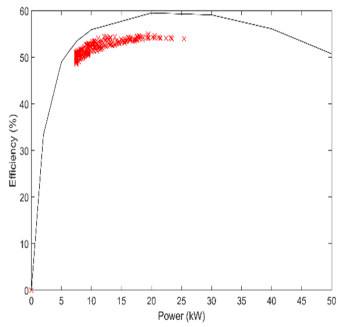

Figure III.36: Fuel cell vehicle efficiency for the UDDS driving cycle.

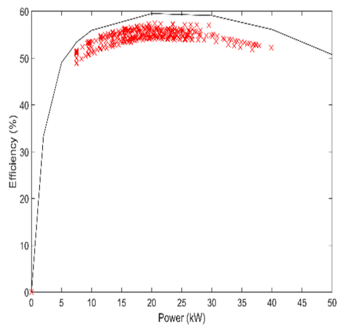

Figure III.37: Fuel cell vehicle efficiency for the US06 driving cycle

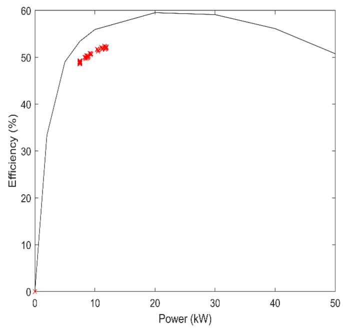

Figure III.38: Fuel cell vehicle efficiency for the CYC_CBD14 driving cycle

III.5.4.2 FC + Supercapacitor Configuration

In the second scenario, involving hybridization with a supercapacitor:
During the UDDS cycle (Figure III.39), the fuel cell vehicle achieves an efficiency between 46% and 59%, managing power demands in the range of 7 to 34 kW.
For the US06 cycle (Figure III.40), the efficiency ranges from 47% to 60%, effectively coping with energy demands between 7 and 35 kW.
In the CYC_CBD14 cycle (Figure III.41), the efficiency ranges from 48% to 55%, supporting a power range of 7 to 13 kW.
This hybridization confirms the effectiveness of using supercapacitors in highly dynamic driving conditions, ensuring rapid response during energy spikes and deceleration recovery.

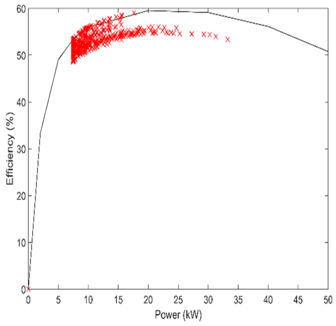

Figure III.39: Fuel cell vehicle efficiency for the UDDS driving cycle

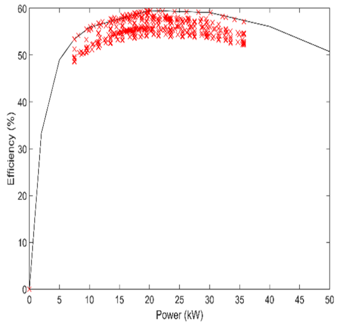

Figure III.40: Fuel cell vehicle efficiency for the US06 driving cycle

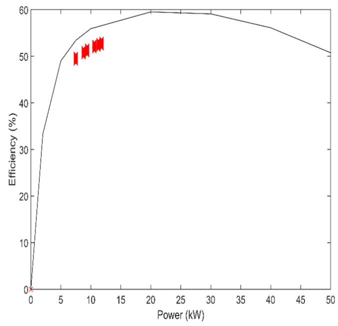

Figure III.41: Fuel cell vehicle efficiency for the CYC_CBD14 driving cycle

III.5.4.3 FC + Lead-Acid Battery Configuration

For the third hybridization scheme with a lead-acid battery:
In the UDDS cycle (Figure III.42), efficiency ranges from 47% to 59%, supplying power in the range of 7 to 30 kW, aligning well with the cycle's moderate acceleration phases.
For the US06 cycle (Figure III.43), the system achieves efficiency between 46% and 59%, sustaining power outputs up to 39 kW during high-load phases.
In the CYC_CBD14 cycle (Figure III.44), efficiency ranges from 48% to 54%, meeting the typical low-speed, high-frequency start-stop conditions of urban driving.

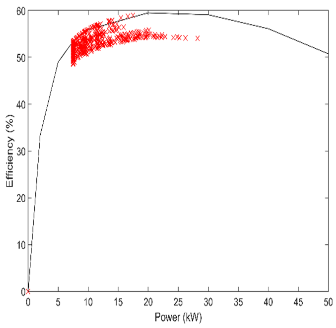

Figure III.42: Fuel cell vehicle efficiency for the UDDS driving cycle

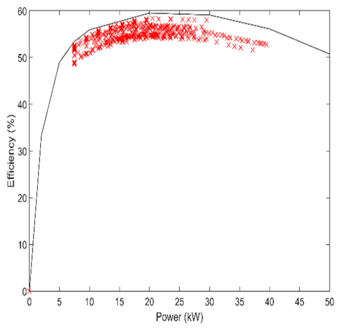

Figure III.43: Fuel cell vehicle efficiency for the US06 driving cycle

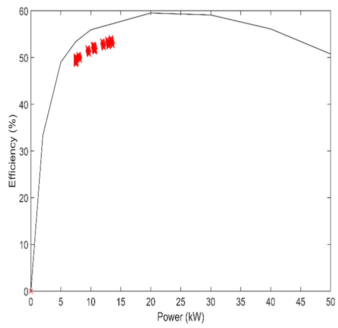

Figure III.44: Fuel cell vehicle efficiency for the CYC_CBD14 driving cycle

The results from all hybridization settings confirm the efficacy of the suggested energy management algorithm. The synergy between fuel cells and secondary energy storage devices, including lithium-ion batteries, supercapacitors, and lead-acid batteries, has been unequivocally established. The hybrid designs satisfy power requirements during all evaluated driving cycles while preserving appropriate final state-of-charge levels, guaranteeing preparedness for following driving cycles.

The analysis also confirms that the fuel cell is activated predominantly during periods of high load. In contrast, during low-demand phases (e.g., initial acceleration), energy is predominantly drawn from the batteries or supercapacitors due to their faster response time. The hybrid configurations implemented reduce the fuel cell's reaction time by approximately 40%, enhancing transient response and overall system efficiency.

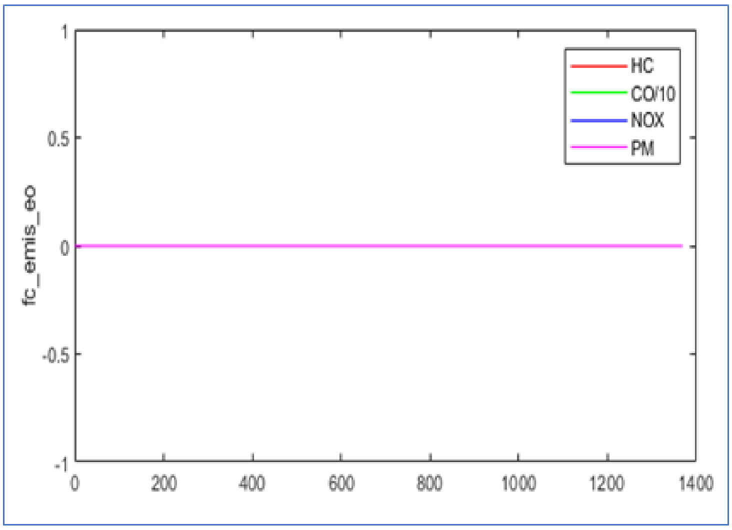

Figure III.45: Gas emissions from the fuel cell vehicle with the studied configurations.

Figure III.45 illustrates the gas emissions from the fuel cell vehicle throughout the three examined configurations, classifying them into hydrocarbons (HC), carbon monoxide (CO/10), nitrogen oxides (NOx), and particulate matter (PM). All emission curves have a virtually horizontal trajectory, remaining close to zero, signifying very low emissions. The projected decrease surpasses 90% in comparison to traditional ICE automobiles. These results underscore the ecological benefits and sustainability of fuel cell electric vehicles (FCEVs) as feasible substitutes for fossil fuel-dependent transportation systems.

The examination of many hybridization methodologies demonstrates that integrating fuel cells with different energy storage technologies significantly improves energy efficiency and system responsiveness. It emphasizes the significance of choosing energy storage systems that align with their dynamic response attributes for various driving conditions. Furthermore, the substantial decrease in emissions reinforces fuel cell cars as a viable alternative for greener urban transportation, in accordance with global sustainability and decarbonization objectives.

III.6 Conclusion

This chapter demonstrates the essential role of energy management strategies in fuel cell electric vehicles. By integrating the fuel cell with various energy storage systemslithium-ion batteries, supercapacitors, and lead-acid batteriesthe study demonstrates improved efficiency, reliability, and adaptability under diverse driving conditions. The implemented Energy Management System , utilizing the ADVISOR platform, optimized the monitoring, control, and balancing of hybrid energy sources, thereby reducing energy losses and emissions. The results validate that dual-source hybridization and optimized management strategies significantly enhance vehicle autonomy, component lifespan, and overall system performance.

Looking ahead, adopting intelligent control techniques and fault-tolerant strategies could further boost the resilience and sustainability of FCEVs, paving the way for advanced, adaptable, and environmentally friendly mobility solutions.

Chapter IV

Fuzzy Logic Control and Optimization for Hybrid Parallel Electric Vehicle Systems

IV.1 Introduction

The growing need for sustainable transportation has intensified research into advanced powertrain technologies that can reduce fuel consumption and minimize environmental impact. Among these technologies, Hybrid Electric Vehicles (HEVs) have emerged as a promising solution, as they combine the benefits of conventional internal combustion engines with electric propulsion systems. By intelligently managing the interaction between the different sources of energy, HEVs can achieve significant improvements in terms of energy efficiency, emissions reduction, and overall driving performance.

Parallel Hybrid Electric Vehicles (P-HEVs) represent one of the most widely studied hybrid architectures due to their structural simplicity and ability to optimize energy flow under diverse driving conditions. However, achieving efficient energy management in such vehicles remains a complex challenge due to the nonlinear dynamics of the system, the stochastic behavior of driving cycles, and the trade-offs between conflicting performance objectives, such as fuel economy, emissions reduction, and battery state-of-charge (SOC) stability.

In this context, intelligent control methods have gained increasing attention as viable solutions to these challenges. Among them, fuzzy logic has proven particularly effective due to its ability to handle uncertainties, nonlinearities, and imprecise data within the hybrid powertrain system. Unlike conventional rule-based or deterministic control strategies, fuzzy logic-based strategies offer robust adaptability under real-world driving conditions. Nevertheless, while many studies highlight the potential of fuzzy logic controllers, critical research gaps remain concerning their optimization, validation, and scalability for complex hybrid powertrain configurations.

The present research is motivated by the need to address these gaps through a comprehensive analysis of fuzzy logic energy management strategies and their integration with advanced optimization techniques. By systematically evaluating multiple fuzzy strategiesranging from efficiency-oriented to emission- and fuel-oriented designsthis study investigates performance trade-offs using standardized driving cycles and simulation tools. Furthermore, the incorporation of evolutionary algorithms, such as Genetic Algorithms (GAs), provides a pathway to multi-objective optimization, enabling more balanced strategies that align with both environmental and efficiency goals.

Ultimately, this work aims to deliver both theoretical and practical contributions to the field of hybrid vehicle energy management. From a scientific perspective, it offers insights into the design, evaluation, and optimization of fuzzy logic-based controllers. From an engineering standpoint, it supports automotive designers and researchers in developing next-generation energy management systems that enhance the viability of hybrid technologies as a cornerstone of sustainable mobility.

IV.2 Hybrid Electric Vehicles (HEVs)

Modern advancements in transportation have transformed mobility and enhanced daily life. While the ICE has played a crucial role in automotive development, its emissionsincluding carbon dioxide (CO_2), carbon monoxide (CO), nitrogen oxides (NOx), and unburned hydrocarbons (HCs)have raised significant environmental concerns such as air pollution, global warming, and ozone layer depletion [75]. These pollutants threaten both public health and ecosystems, while the finite nature of petroleum reserves has necessitated the exploration of sustainable alternatives to petroleum. In response, electric vehicles (EVs), extended-range electric vehicles (EREVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs) have emerged, offering reduced emissions, improved fuel efficiency, and decreased reliance on fossil fuels 66.

To maximize energy usage, HEVs combine two or more power sources, typically a generator and an ICE. Their dynamic powertrain utilizes a battery to store and discharge energy, allowing for seamless switching between the electric motor and the ICE to enhance fuel efficiency and reduce emissions [38]. The increasing adoption of HEVs is driven by their efficient electric motors, sophisticated control systems, and ability to harness alternative energy sources [63]. Historically, the foundation for this technology was laid by EVs, with Gustave Trouvé's 1881 invention of the first electric vehicle, powered by a 0.1-horsepower motor and lead-acid batteries [29]. While electric vehicles provide clean and efficient urban transportation, their limited range is an issue that hybrid electric vehicles were invented to address [49].

By combining the strengths of ICEs and electric motors, HEVs mitigate their respective limitations. Their battery-assisted power source reduces fuel consumption and emissions, enhancing overall vehicle efficiency [28]. The initial gasoline-electric hybrid, known as the Lohner-Porsche Mixte Hybrid, was created by Ferdinand Porsche in 1901. In contrast to electric vehicles, hybrid electric vehicles do not require charging from an external source; instead, their batteries are recharged through regenerative braking or the internal combustion engine. Nonetheless, this restricts their electric range and requires longer journeys to recharge [69].

PHEVs address this limitation by incorporating a larger battery that can be recharged from the electrical grid, further improving fuel efficiency and reducing dependency on liquid fuels. The ability to charge from standard outletseither at home or public charging stationsmakes PHEVs an attractive, cost-effective, and environmentally friendly alternative. Their enhanced battery capacity offers superior fuel economy and lower emissions, reinforcing the shift toward sustainable transportation [34].

Understanding powertrain topologies is crucial for formulating effective energy management optimization strategies. Transmission designs vary based on power source connectivity, whether mechanical or electrical. HEV powertrains exist in three main configurations: (1) series, (2) parallel, and (3) series-parallel. (See section I.3, (Electric vehicle typologies)).

IV.3 Modeling the vehicle's power system

To properly assess a suggested EMSys, a precise dynamic model of a HEV is essential. Engineers and academics may test and evaluate EMS performance in a variety of circumstances thanks to this model, which converts intricate real-world systems into mathematical representations. Such modeling enables a thorough evaluation of energy management strategies by providing in-depth insights into system behavior and responses under various operating conditions.

There are several significant advantages to creating a comprehensive dynamic model for an HEV. It makes it possible to thoroughly analyze how various vehicle partslike the battery, electric motor, and ICE interact with one another, providing a comprehensive picture of how the HEV behaves under various driving circumstances, including changes in speed, acceleration, power consumption, and energy regeneration. This integrated approach supports performance analysis by allowing engineers to evaluate the efficiency of individual components and assess the influence of environmental factors on overall system performance. Conducting these analyses before real-world implementation ensures that the EMS operates optimally, maximizing energy efficiency and minimizing emissions across diverse scenarios.

In parallel hybrid electric vehicles, the ICE and the primary electric motor are configured in parallel, enabling independent operation. This setup supports four driving modes:

1. The primary electric motor alone (EV1) for low speeds or light loads,
2. The ICE alone (EV2) for high speeds or heavy loads,
3. A combination of the electric motor and ICE (EV3) for very high speeds or loads, and
4. A combined mode involving the primary electric motor, a generator motor, and the ICE (EV4) for extremely high speeds or loads.

A mid-size family passenger HEV, incorporating advanced technologies typical of parallel configurations, is illustrated in Figure IV.1.

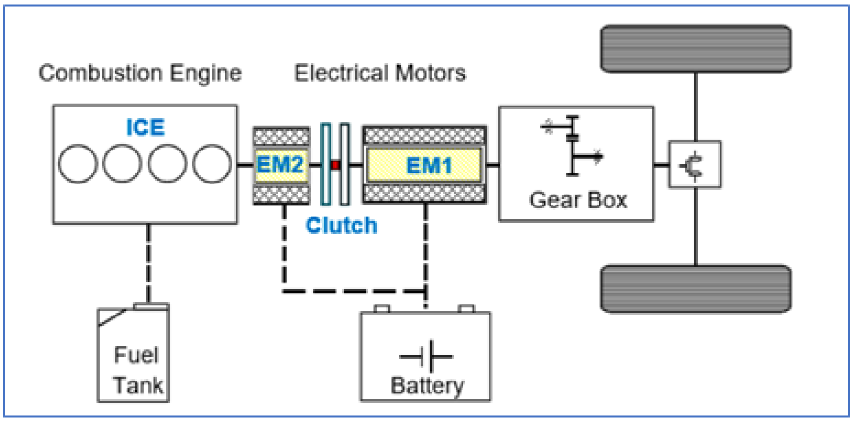

Figure IV.1: Parallel HEV [71].

Figure IV.1 can be modelled as a simple transmission, shown in Figure IV.2. This mechanical structure is divided into three sections. The first section comprises the internal combustion engine (ICE) and the starting electric motor/generator (EM2), grouped as a single inertia, which encompasses the left clutch disc, shaft 1, and ICE. A rigid inertia models this section, J_1, with torques M_{ICE} and $M_{(EV1)}$ applied to the ICE and EM2, respectively, and angular parameters θ_1 and ω_1 corresponding to the position and speed of shaft 1.

The second part represents the rigid inertia J_2, concentrating the main electric motor (EM1) and the right-hand clutch. The angular position and speed of shaft 2 are denoted by θ_2 and ω_2. Finally, the third part links the gearbox to the drive wheels via a gear ratio i and a torsion spring damped by a stiffness coefficient k_α, k_β and damping coefficients k_θ, with J_3 as the concentrated inertia for the rest of the vehicle (including gearbox, differential, shaft 3, and wheels). The parameters θ_3 and ω_3 indicate the angular position and speed of shaft 3, while r_S is the rolling radius of the vehicles wheels.

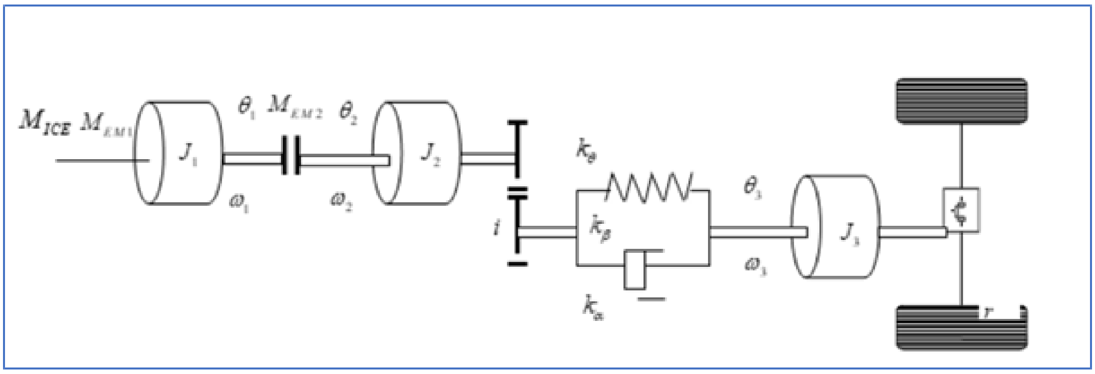

Figure IV.2: Simplified structure of the parallel HEV [71].

Approximations of the air density (ρ), air drag coefficient (C_w), vehicle crossing area (A), wheel rolling radius (r_r), vehicle friction resistant coefficient (f_r), natural gravity (g), vehicle mass (m), and the polynomial coefficients of a_0, a_1, and a_2 approximate the vehicle resistance torque. It is possible to compute the vehicle rolling resistance torque M_v as:

$$M_v = \left(\frac{\rho}{2} C_w A (r\omega_3)^2\right) + f_r mg + a_0 + a_1\omega_3 + a_2\omega_3^2 \tag{IV.1}$$

The vehicle rolling resistance torque can be altered by adding other road parameters, such as road dynamics, road increase, and other environmental factors, to Equation (1) [70, 71] Discuss how changes in road conditions and vehicle dynamic limitations between the steering wheel and vehicle speed can affect a vehicle's velocity.

Only the primary electric motor, EM1, drives the HEV while the clutch is open, at a low speed of less than 40 km/h. Some other exponential coefficients have a negligible influence and can be disregarded. At low speeds, the vehicle's rolling resistance torque can be expressed simply as:

$$M_v = M_{v0} + k_v\omega_3 \tag{IV.2}$$

where M_{v0} is the initial resistance constant of air drag and rolling friction, and k_v is a linear coefficient that depends on the gear ratio.

On the first part, the torque applied is:

$$M_{1o} = J_1\dot{\omega}_1 \tag{IV.3}$$

This torque can be calculated as:

$$M_{1o} = M_{ICE} + M_{M2} - M_c \tag{IV.4}$$

M is the torque from the ICE, M_{M2} is the torque from motor ME2, and M_c is the torque from the clutch.

When the clutch is locked, the clutch torque M_c is the maximum static clutch friction:

$$M_c = \frac{2}{3} r_c F_{Nc}\mu_s \quad \text{when } (M_c < M_{static\_f\_max}) \tag{IV.5}$$

where r_c is the clutch radius, F_{Nc} is the normal force, and μ_s is the clutch friction coefficient.

When the clutch is in the transitional period, $(M_c < M_{static\_f\_max})$, the clutch torque is:

$$M_c = r_c F_{Nc}\,\mathrm{sign}(\omega_1 - \omega_2)\,\mu_k \quad \text{when } (M_c < M_{static\_f\_max}) \tag{IV.6}$$

where μ_k is the clutch slipping coefficient.

On the second part, the torque applied to the primary motor ME1 is:

$$M_{2o} = k_\theta\theta_2 + \frac{k_\theta}{i}\theta_3 + k_v\omega_3 \tag{IV.7}$$

The sum of inertias is calculated as:

$$M_{2o} = J_2\dot{\omega}_2 i + J_3\dot{\omega}_3 + k_v\omega_3 \tag{IV.8}$$

The torque change is calculated as follows:

$$\dot{M}_{2o} = J_2\dot{\omega}_2 i + k_\alpha\left(\frac{\dot{\omega}_2}{i} - \dot{\omega}_3\right) + k_\beta\left(\frac{\omega_2}{i} - \omega_3\right) \tag{IV.9}$$

Finally, the balance of change M_{2o} is calculated as:

$$M_{2o} = (M_{EM2} + M_c)\eta_i - M_{v0} \tag{IV.10}$$

where η_i is the transmission efficiency of the gearbox and the differential gear.

Based on these equations and dynamic relationships, it is possible to design energy management strategies adapted to the different operating modes of a parallel HEV. These strategies consider environmental conditions, mechanical constraints, and component behavior to achieve an optimal balance between fuel consumption, electrical autonomy, and reduced pollutant emissions.

IV.4 Control Strategies and Algorithms for Energy Management

We develop a simulation and modeling of the Powertrain of a Parallel Hybrid Electric Vehicle (P-HEV) using ADVISOR Software. The tool is designed in [70, 71]. ADVISOR is a fuel cell, hybrid, or electric vehicle simulator that operates within the MATLAB/Simulink environment. It's a tool that applies a hybrid forward-backward simulation method, enabling the real-time dynamic estimation of power requirements for automobile components.

ADVISOR enables real-time analysis and modification of control strategy testing due to its intuitive interface and modular structure. This work utilizes these features to develop an accurate PHEV powertrain model that is sophisticated enough to enable the evaluation of the proposed EMSys [68] while being optimized to improve reliability.

IV.4.1 Vehicle Configuration

The PHEV model features an ICE, electric motors, and an Energy Storage System (ESS), which can operate separately or in conjunction, depending on the instantaneous driving situation. The scope of work involves evaluating the performance of major systems, including the ICE, electric motors, and battery, to assess their strengths and weaknesses in terms of energy use efficiency, exhaust emissions, and fuel consumption. The PHEV's mechanical components, along with its energy structure and configuration, are thoroughly examined to ensure a robust and comprehensive assessment of its functioning through simulation.

IV.4.2 ADVISOR Implementation

The PHEV model (Figure IV.3) is developed using MATLAB/Simulink, incorporating both mechanical and energy subsystems. The parameter definitions (Figure IV.4) include crucial attributes such as vehicle mass, frontal area, propulsion type, fuel and energy storage specifications, and dynamic coefficients, all of which are vital for evaluating energy consumption, range, and overall vehicle dynamics. These elements contribute to optimizing the vehicle's operation in both electric and hybrid modes.

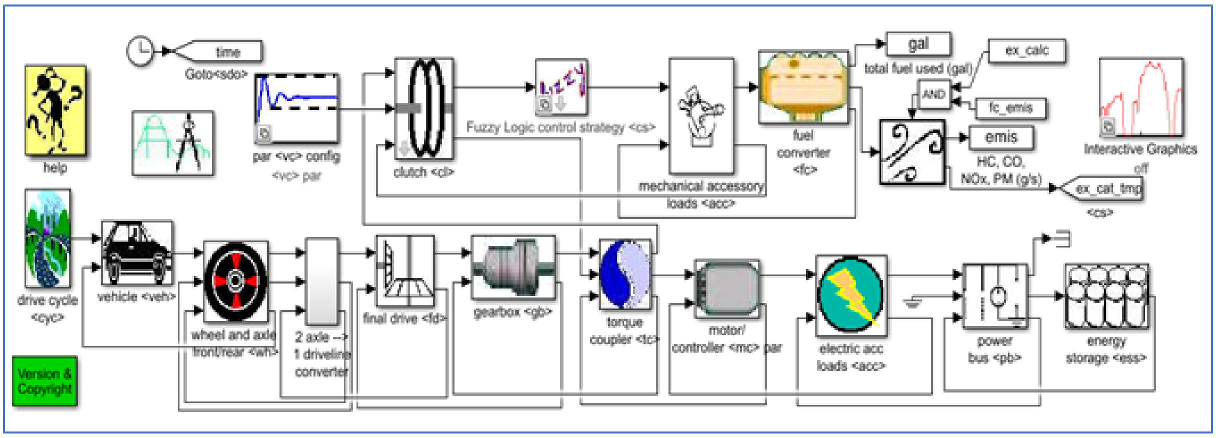

Figure IV.3: Parallel HEV model in ADVISOR/Simulink.

IV.4.3 Energy Management Strategies

To enhance energy efficiency and operational effectiveness, this study explores five fuzzy logic-based EMS strategies:

1. **Fuzzy Efficiency Mode** : Prioritizes energy efficiency under varying driving conditions.
2. **Fuzzy Emissions Mode** : Focuses on minimizing pollutant emissions.
3. **Fuzzy Fuel Mode** : Aims to reduce overall fuel consumption.
4. **Custom Fuzzy Logic Strategy** : Introduces a novel rule-based system tailored to meet specific operational requirements.
5. **Optimized Custom Strategy** : Employs a genetic algorithm to fine-tune the fuzzy logic strategy for multi-objective optimization.

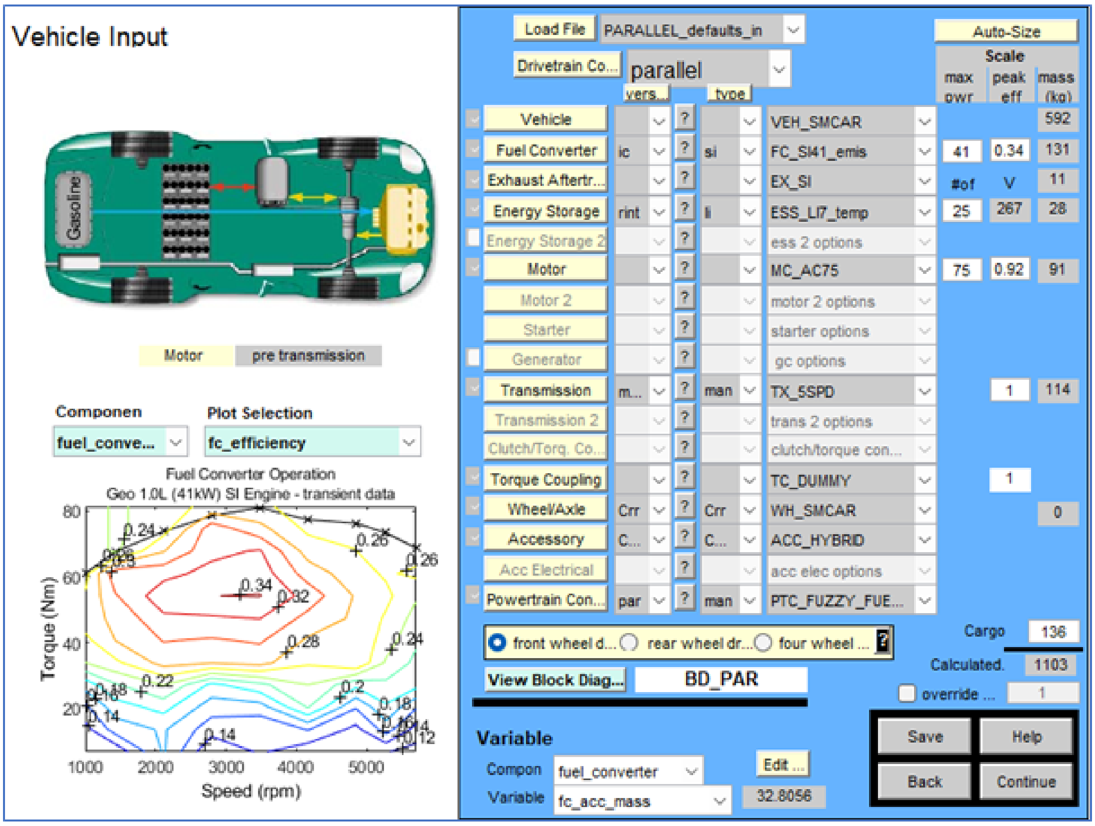

Figure IV.4: Key PHEV parameters for simulation.

IV.5 Comparative Analysis and Performance Evaluation

The study conducts a comparative analysis of these five strategies based on the following performance metrics:

- **Energy Efficiency:** Assessing how effectively the vehicle utilizes stored energy.
- **Emissions Reduction:** Evaluating levels of CO2 and NOx emissions under different EMS strategies.
- **Fuel Economy:** Measuring fuel consumption across different driving cycles.
- **Battery SOC Management:** Ensuring optimal energy storage utilization.

The evaluation is conducted across multiple driving scenarios, including ARB02 (urban/suburban) and highway cycles, to validate real-world performance. Furthermore, optimization techniques, such as Pareto-front analysis, are employed to balance trade-offs between fuel economy, emissions, and energy efficiency, ensuring a comprehensive assessment of the proposed EMS strategies.

IV.5.1 Fuzzy Efficiency Mode (FEM)

Fuzzy Efficiency Mode (FEM) is designed to maximize the overall energy efficiency of a HEV system. It emphasizes optimal operation within the efficiency zones of key components, such as the internal combustion engine and electric motor , with the primary goal of minimizing energy losses during mechanical and electrical conversions. FEM performs exceptionally well in driving cycles characterized by frequent power transitions, such as those found in urban environments.

The FEM rule base is structured around input parameters, including battery State of Charge [%] (SOC), consumption of power, and vehicle speed. Examples of rules include:

- If power demand is low and SOC is high, the electric motor is prioritized to leverage its efficiency.
- At high speeds with elevated torque demand, the ICE operates solely within its optimal efficiency range.

A comprehensive set of specific rules ensures precise performance optimization. The Fuzzy Control Block for FEM, depicted in Figure IV.5, processes input torque and speed demands (cs_trq_in_r and cs_spd_in_r) through scaling and fuzzy logic operations to enhance energy efficiency. This dynamic adjustment ensures that the ICE and EM operate within their peak efficiency zones, minimizing losses, particularly in urban driving scenarios with frequent transitions.

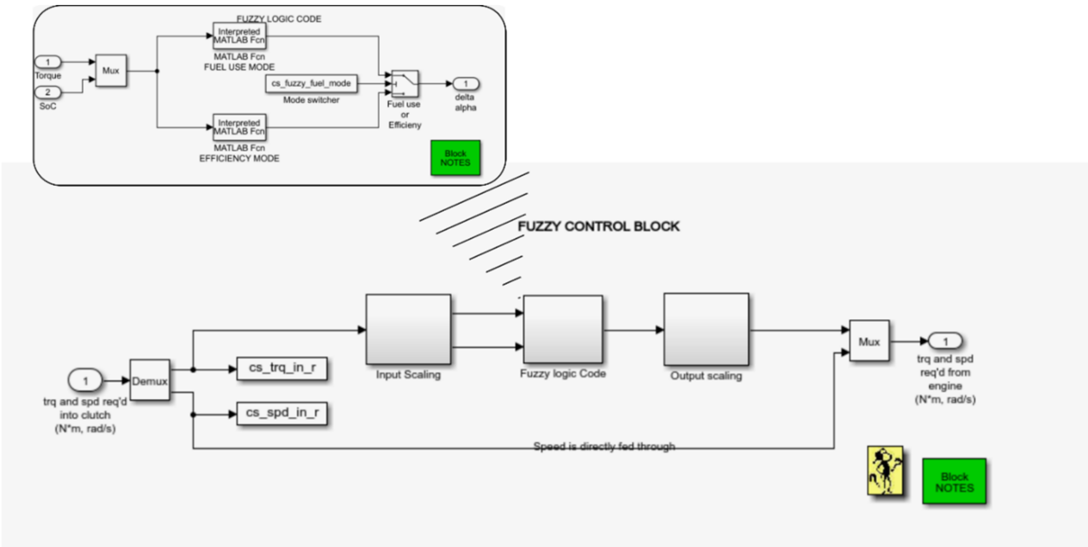

Figure IV.5: Fuzzy Control Block (FEM)

IV.5.2 Fuzzy Emissions Mode (FEMO)

Fuzzy Emissions Mode (FEMO) prioritizes the reduction of pollutant emissions by favoring energy configurations that minimize the environmental impact of the ICE. It promotes the use of electric motors in urban settings, reducing the frequency of ICE startups and shutdownsknown to produce elevated emissionsand maintains ICE operation at minimal emission levels when required.

FEMO employs rules centered on stringent emission thresholds, such as:

- At low loads, the ICE is bypassed to curb NOx emissions.

- If SOC is low, the ICE engages at a compensatory load but is restricted to speeds yielding minimal emissions.

Complex membership functions enable FEMO to strike a balance between efficiency and environmental performance. The Fuzzy Control Block for FEMO, shown in Figure IV.6, dynamically adjusts energy flows between the ICE and EM based on inputs such as engine speed, load, and SOC. By ensuring the ICE operates only within low-emission zones, FEMO significantly reduces NOx and CO emissions, particularly during urban driving.

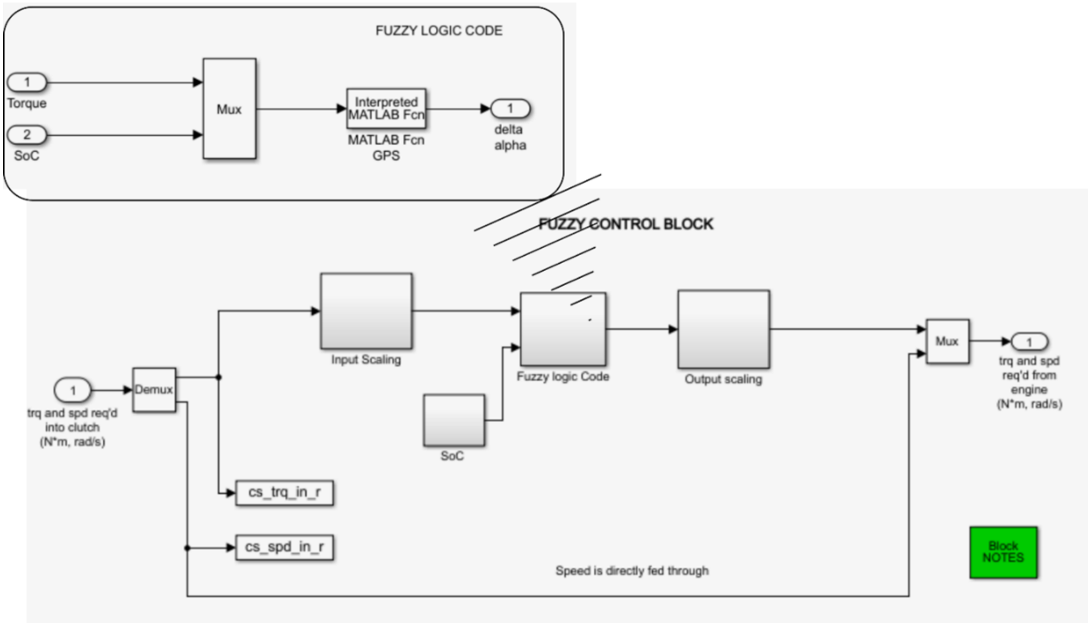

Figure IV.6: Fuzzy Control Block (FEMO)

IV.5.3 Fuzzy Fuel Mode (FFM)

Fuzzy Fuel Mode (FFM) aims to minimize fuel consumption by maximizing electric motor utilization and extending periods when the ICE remains inactive. This strategy excels in driving cycles with stable, moderate engine speeds, such as those found on highways.

FFM's rules promote maximum electric autonomy, including:

- If SOC is sufficient, the ICE remains deactivated until critical power or SOC thresholds are reached.

- When activated, the ICE operates within its minimum specific fuel consumption zone.

The FFM Fuzzy Control Block, shown in Figure IV.7, maximizes fuel efficiency by looking at input parameters of driving speed, SOC, and torque demand. When low power demand exists, the internal combustion engine is completely decoupled, and the electric motor can provide propulsion as long as the state of charge falls within safeguard parameters.

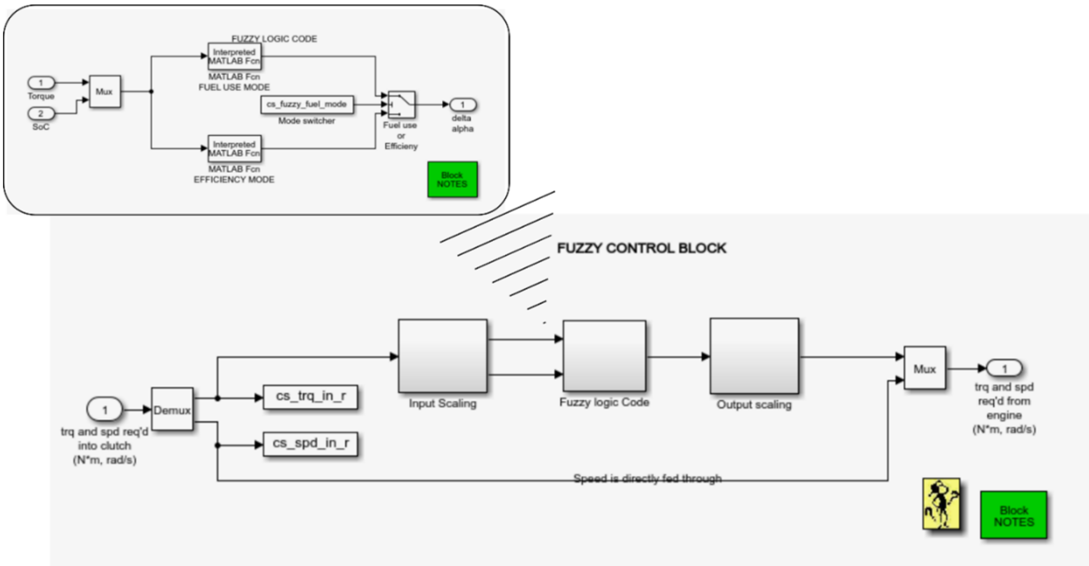

Figure IV.7: Fuzzy Control Block (FFM)

IV.5.4 Fuzzy Logic-Based Control Strategy (FLCS) for Energy Management

Fuzzy logic is a well-developed method of controlling complicated systems. In this work, an EMSys is employed to facilitate the efficient operation of HEVs. This custom-designed module serves as a decision controller, regulating energy transfers with respect to operation conditions and demand changes.

The proposed system utilizes:

- **The Two Input Variables:**
  - Battery state of charge (SOC), categorized into three linguistic levels: Low (L), Medium (M), and High (H).
  - Required torque (req-Torque), represented by five levels: Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH).

- **One Output Variable:**
  - Out-torque (generated torque), which is optimized to equalize energy demand with optimal efficiency and minimal loss.

The fuzzy logic at Mamdani conceives a system of decision-making rules that optimize performance while being able to take into account the uncertainties of execution conditions. Defuzzification is performed using the centroid method, enabling a smooth transition from fuzzy values to precise control values. As shown in Figure IV.8 to Figure IV.11, each variable moves within its own defined area with specific limit values. This fuzzy domain allows for robust and flexible management of dynamic changes in hybrid electric vehicles (HEV).

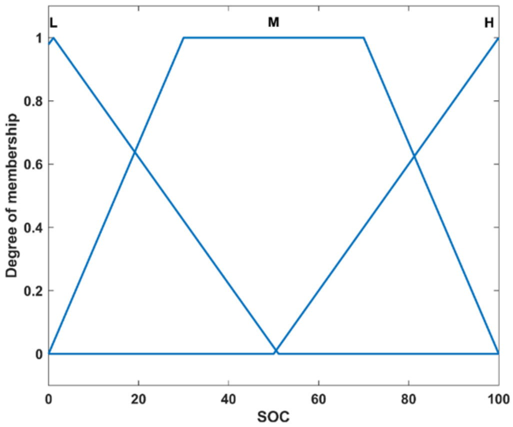

Figure IV.8: Membership functions for state of charge (SoC).

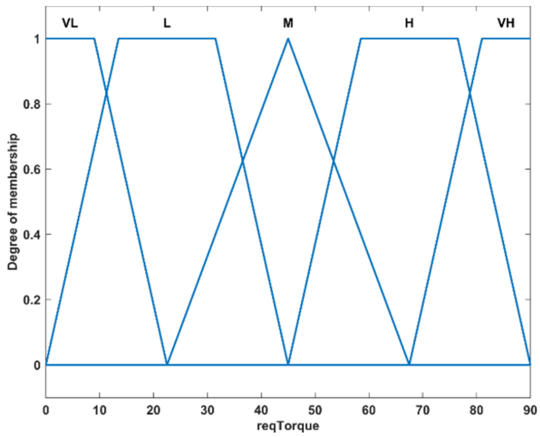

Figure IV.9: Membership functions for the required pair (*reqTorque*).

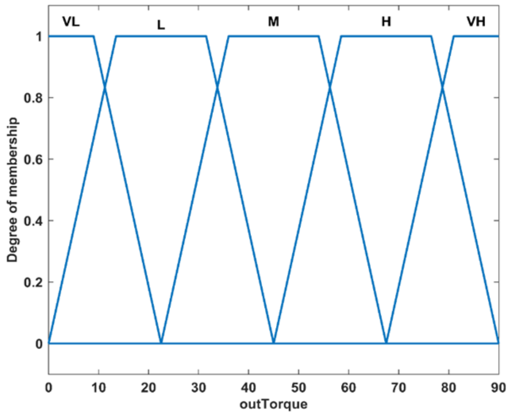

Figure IV.10: Membership functions for the generated pair (*outTorque*).

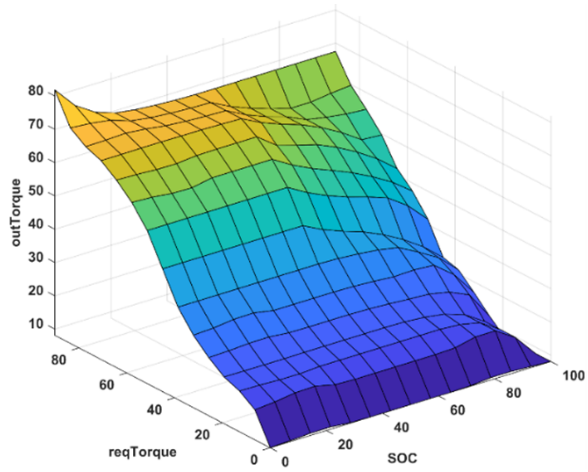

Figure IV.11: Fuzzy output surface.

The implementation of this original approach, based on fuzzy logic, is founded on a comprehensive set of decision rules, which, as noted, constitute the core of the system's decision-making process. Using the Mamdani inference method, these rules perform the associator function of input variables (required SOC and torque) to output variable (output torque), which gives these requirements flexibility to adapt to operational conditions and time-of-flight uncertainties. All the efforts made to minimize system consumption and ensure its stability result in each rule being based on a logic between the states of input and output. The set of fuzzy decision rules described in this work is detailed in table IV.:

Table IV.1: List of Fuzzy Rules

No.	SOC	reqTorque	outTorque
1	Low (L)	Very Low (VL)	Very Low (VL)
2	Low (L)	Low (L)	Low (L)
3	Low (L)	Medium (M)	Medium (M)
4	Low (L)	High (H)	High (H)
5	Low (L)	Very High (VH)	Very High (VH)
6	Medium (M)	Very Low (VL)	Very Low (VL)
7	Medium (M)	Low (L)	Low (L)
8	Medium (M)	Medium (M)	Medium (M)
9	Medium (M)	High (H)	High (H)
10	Medium (M)	Very High (VH)	Very High (VH)
11	High (H)	Very Low (VL)	Very Low (VL)
12	High (H)	Low (L)	Low (L)
13	High (H)	Medium (M)	Medium (M)
14	High (H)	High (H)	High (H)
15	High (H)	Very High (VH)	Very High (VH)

IV.5.5 Optimization Algorithm for Enhancing Fuzzy Logic-Based Energy Management Strategies

Often, integration of optimization algorithms helps to enhance the efficiency of fuzzy logic-based energy management techniques. These algorithms optimize parameters, such as sub-assembly functions, rule bases, and scale factors, thereby achieving objectives like reducing fuel consumption, emissions, or energy losses. A detailed analysis of the genetic optimization algorithm (GA) is presented, as it is the most common approach in these problems.

IV.5.5.1 Genetic Algorithm (GA)

The GA is a stochastic optimization technique based on the theory of natural selection as well as on the principles of genetics and evolution. Proposed by John Holland in the 1970s, GA mimics biological processes of evolution, such as reproduction and mutation, to find and optimize complex spaces. In a GA, a population of candidate solutions (often referred to as individuals or chromosomes) progresses over generations. Each individual is assessed based on a fitness function, and the best-performing individuals are selected for breeding to form the next generation. Over time, this iterative cycle allows GGAs to converge towards an optimal or near-optimal solution.

The fundamental concept of GAs is closely tied to two areas of research: evolutionary computation, which simulates natural processes to solve optimization problems, and artificial intelligence, which uses heuristic methods to explore significant and complex search spaces [6].

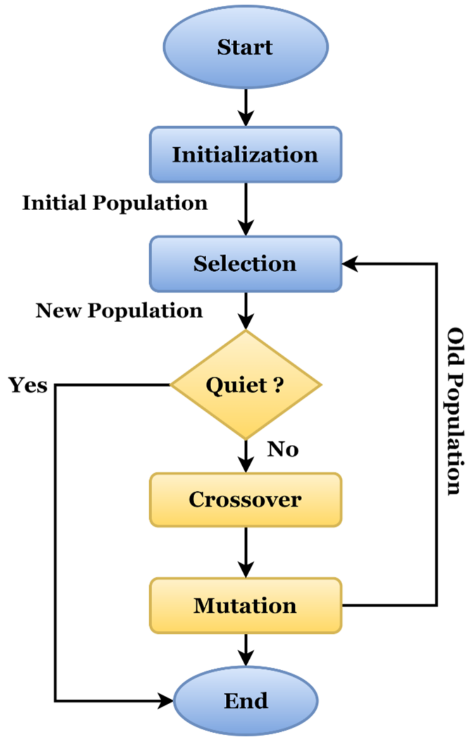

Figure IV.12: Genetic Algorithm optimization algorithm flow chart

Within the framework of applying GAs to optimization problems, five essential principles can be identified:

- **Selection:** The algorithm must prioritize fitter individuals to ensure better genetic material is passed to the next generation.
- **Crossover:** It must combine the genetic information of parents to produce new offspring with potentially improved traits.
- **Mutation:** It introduces diversity by randomly altering genetic material, preventing premature convergence.
- **Fitness Evaluation:** It must assess the quality of each individual based on an objective function.
- **Diversity Maintenance:** The population must maintain genetic diversity to explore the search space effectively.

Numerous experiments have demonstrated that GAs are versatile and practical optimization tools for a wide range of applications, as illustrated in the flow diagram of the algorithm presented in Figure IV.12[62].

Figure IV.12 illustrates the general flow of the Genetic Algorithm (GA) process in diagrammatic form. The algorithm begins with the initialization of the population, where a set of candidate solutions (called chromosomes) is randomly generated in the search space. Each chromosome is then evaluated using an objective function to measure its performance. Based on the fitness values, a subset of chromosomes (using methods such as proportional selection or tournament) is selected to participate in reproduction. The selected chromosomes undergo crossover operations, combining parts of two parents to produce offspring, and mutations, which introduce minor random modifications to explore new solutions in the search space. After these steps, a new population is formed to replace the old one. This iterative process continues until the stopping criterion is satisfied, such as reaching a maximum number of generations or convergence towards an optimal solution. The algorithm thus leverages the principles of natural evolution to find a solution adapted to the given problem efficiently.

IV.5.5.2 Comprehensive Fuzzy Logic-Based EMS Optimization

Fuzzy logic systems are well-suited for handling complex systems such as hybrid energy systems. However, their performance strongly depends on appropriate parameter selection and tuning. Traditional approaches often rely on trial-and-error procedures to adjust fuzzy parameters, which can be time-consuming and may not guarantee optimal performance [2]. In fact, fuzzy logic controllers (FLCs) are highly sensitive to several design parameters, including:

- Types of membership functions (e.g., triangular, trapezoidal).
- Number of membership functions for each variable.
- Shapes of membership functions.
- Rule base configuration.
- Rule weights.
- Ranges of fuzzy variables.

To overcome these limitations and enhance system performance, optimization algorithms are employed to automate the tuning process. In the context of fuzzy EMS for fuel cell hybrid electric vehicles (FCHEVs), Genetic Algorithms (GA) are utilized to optimize key parameters such as the rule base, membership function characteristics, and rule weights.

By exploiting the evolutionary search capability of GA, the EMS can be effectively fine-tuned to improve fuel efficiency and overall vehicle performance. The optimization procedure is structured into four main phases:

1. **Phase 1 (MF Type Selection):** Identification of the most suitable membership function types (e.g., triangular or trapezoidal) for each fuzzy variable.
2. **Phase 2 (Fuzzy Variable Universe Optimization):** Determination of the optimal ranges for fuzzy variables.
3. **Phase 3 (MF Parameters Tuning):** Adjustment of the membership function shapes and distributions.

4. **Phase 4 (Rule Weight Optimization):** Optimization of the weights associated with each fuzzy rule.

This automated optimization framework ensures improved EMS performance by systematically tuning critical fuzzy logic parameters.

IV.5.5.3 Genetic Algorithm Parameters

In this study, Genetic Algorithms are employed due to their effectiveness in solving nonlinear and mixed-variable optimization problems. The optimization process is implemented using MATLAB's built-in GA toolbox, with most operators configured using default settings to ensure robustness and reproducibility.

Table IV.2 summarizes the parameters used throughout the optimization process.

Table IV.2: Genetic Algorithm Parameters Used for Optimization

Parameter	**Setting**
Population Size	50
Number of Generations	30
Selection Method	Stochastic Uniform (default)
Crossover Method	Scattered Crossover (default)
Mutation Method	Adaptive Feasible (default)
Elite Count	$\lceil 0.05 \times \text{Population Size} \rceil$
Fitness Scaling	Rank (default)
Termination Criteria	Maximum generations (30)
Tolerance	10^{-6}

IV.6 Drive cycle ABR02

The primary purpose of this ARB02 sub-cycle from ADVISOR (Figure IV.13) is to simulate various vehicle operation scenarios in a city and an urban peri-urban area. This cycle lasts approximately 1800 seconds (30 minutes) and features speed stages that dynamically increase and decrease, with several pauses. These variations, quite pronounced at the beginning, correspond to urban driving difficulties, such as intersections and traffic lights. As this cycle progresses, there are longer intervals where the speed is more constant, corresponding to residential areas or short portions of highways, eventually reaching a speed of about 120 km/h. At its loop level, it is an essential cycle for assessing energy consumption, fuel efficiency, and vehicle emissions by testing energy management strategies under a large number of realistic driving scenarios.

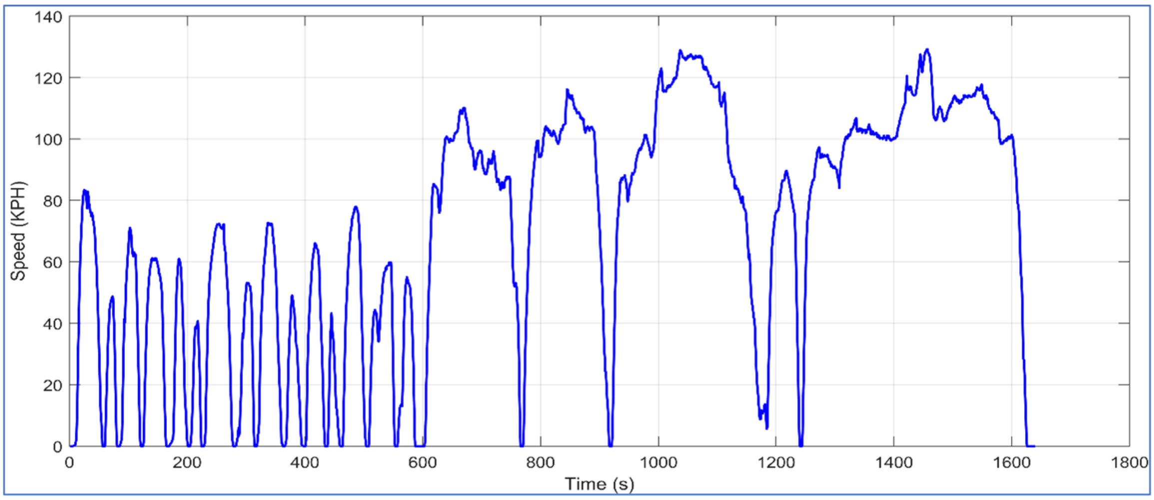

Figure IV.13: The ARB02 Driving cycle

IV.7 Results and Discussions

In this study, five EMS methods for HEVs based on fuzzy logic are evaluated. The first three strategies focus on minimizing fuel consumption, emissions, and increasing energy efficiency. To meet specific operational requirements, a fourth strategy, a Custom Fuzzy Strategy (CFS), introduces customized functions and membership criteria. The fifth technique (CFS-Opt) was created by further optimizing this strategy and offers better performance with this approach. The evaluation of these techniques was conducted in terms of key operational parameters most relevant to the fuzzy logic control approach, including torque distribution, battery central charge state (SOC), and emissions of major pollutants (HC, NOx, CO, PM). The ARB02 hybrid driving cycle was used for testing, which simulates urban and suburban driving with a series of accelerations, decelerations, gear changes, and speed variations.

IV.7.1 Fuzzy Efficiency Mode (FEM) Results

The torque dynamics enable an optimal distribution between the internal combustion engine (ICE) and the electric motor (EM), as illustrated in Figure IV.14. It can be seen that the EM torque varies between -90 and 150 N.m, providing dynamic support during acceleration and deceleration. On the other hand, the torque of the combustion engine remains mainly within the range [0, 80] N.m, with some variations, while operating in its optimal efficiency zones. This strategy aims to minimize energy losses and improve cycle efficiency.

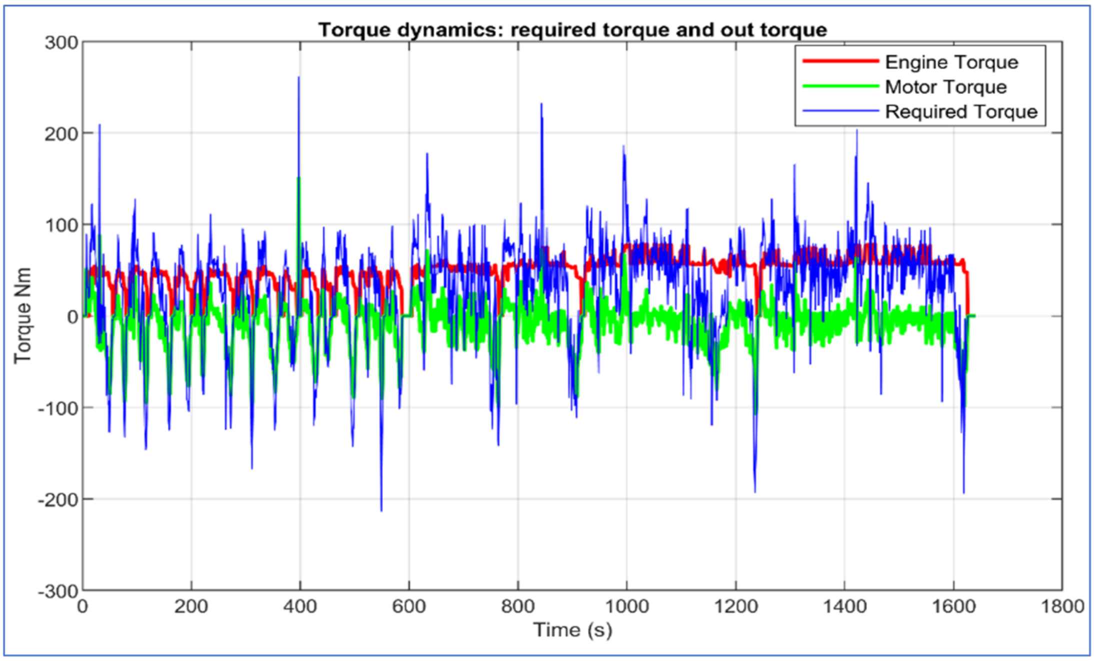

Figure IV.14: Torque Dynamics for FEM

The SoC profile, shown in Figure IV.15, oscillates between a minimum of 55% and a maximum of 70%. Under everyday driving and braking conditions, these values remain within a stable range. However, during phases requiring maximum electrical power, the SoC drops to 55%, which is the minimum tolerable threshold. This drop is compensated for by regenerative braking and strategic activation of the combustion engine. Compared to other strategies, FEM effectively maintains an optimal SoC balance. In contrast, other approaches show more extreme variations, ranging from 20% to 80%, which compromises the durability of the energy storage system.

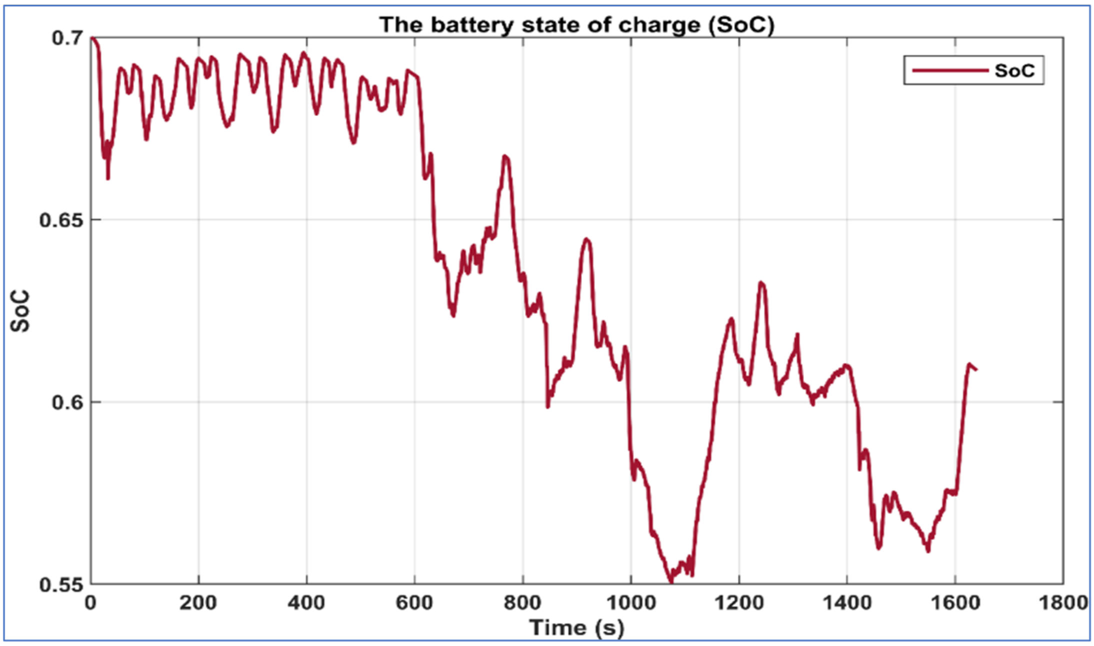

Figure IV.15: Soc for FEM

Figure IV.16 presents the engine-out emissions under FEM:

- **Hydrocarbons (HC) and Particulate Matter (PM):** Remain consistently low due to optimized combustion conditions and reduced ICE activation.
- **Carbon Monoxide (CO):** Peaks are observed during aggressive acceleration phases (e.g., 100-150 sec) due to transient ICE activation but stabilize as driving conditions become steady.
- **Nitrogen Oxides (NOx):** Moderate levels ($\leq$ 45 ppm), indicating that the ICE operates within its controlled emission zones, limiting high-temperature combustion scenarios that contribute to NOx formation.

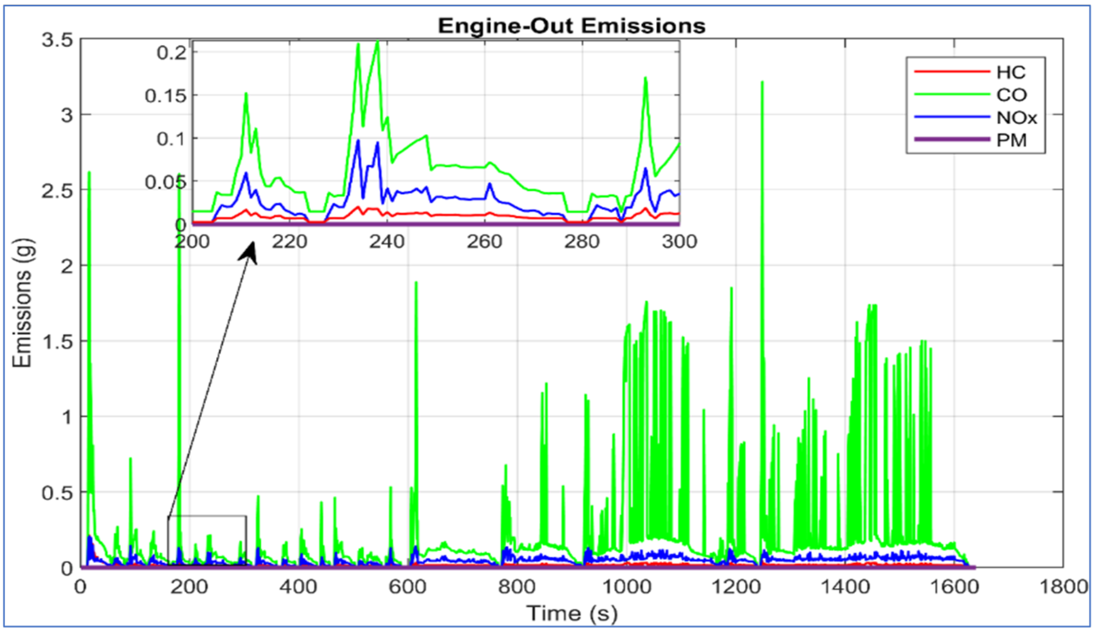

Figure IV.16: Engine-Out Emissions for FEM

The results show that FEM improves energy efficiency by maintaining a good balance between the use of the combustion engine and the electric motor. Fuel consumption is estimated at 6.6 L/100 km, a moderate improvement on the standard strategy based solely on fuzzy logic (6.9 L/100 km). However, there is still room for improvement in certain areas. Although the SoC is maintained within a stable range, further optimizations could be considered to minimize fuel consumption while avoiding rapid fluctuations in the SoC. In addition, although CO and NOx emissions are reduced, adjustments in the management of combustion engine/electric motor transitions could further limit the emission peaks observed during acceleration. These observations underscore the value of an approach that combines fuzzy management and optimization algorithms to enhance the performance of EMS strategies, particularly by dynamically adjusting parameters according to driving conditions.

IV.7.2 Fuzzy Emissions Mode (FEMO) Results

FEMO aims to minimize pollutant emissions while meeting the torque requirements of the ARB02 driving cycle. The results obtained show that FEMO optimizes torque distribution, reduces engine load, and cuts pollutant emissions.

Figure IV.17 illustrates the evolution of the torque distribution required. The torque of the combustion engine varies between 0 and 80 N.m, while that of the electric motor fluctuates between -100 and 120 N.m. This distribution enables the engine to minimize its speed, thereby reducing fuel consumption and limiting the combustion engine's activity during abrupt transitions.

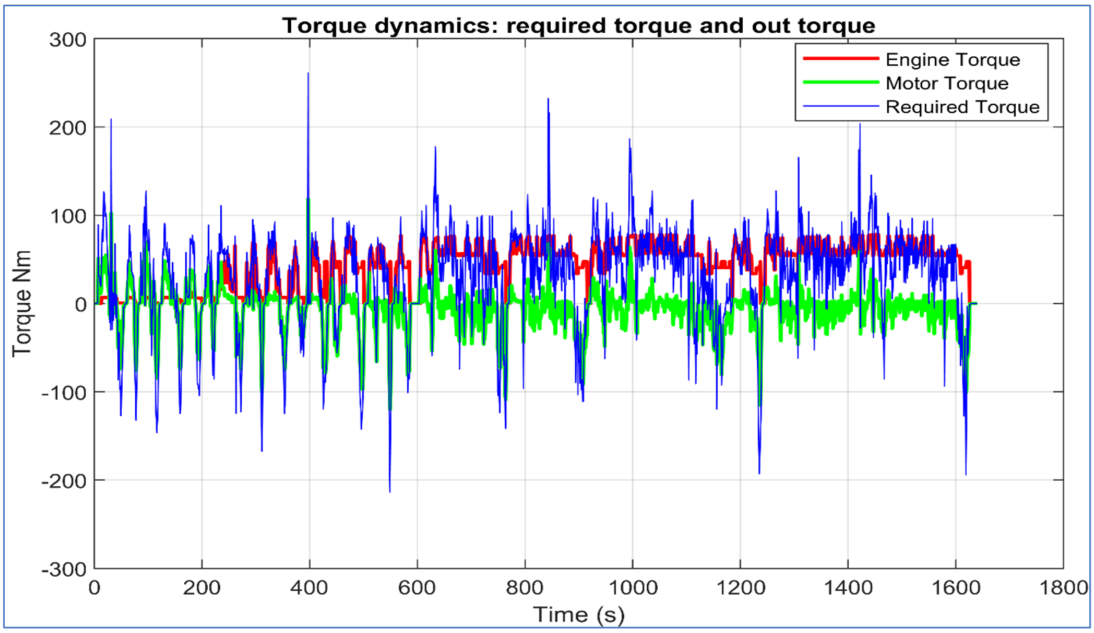

Figure IV.17: Torque Dynamics for FEMO

Figure IV.18 illustrates the evolution of the SoC, which gradually decreases from 70% to 37% over the course of the cycle. This indicates that the electric motor is heavily loaded to prevent overloading the combustion engine. However, the gradual exhaustion of the SoC suggests that the efficiency of regenerative braking could be improved to extend the electric range, particularly on long journeys.

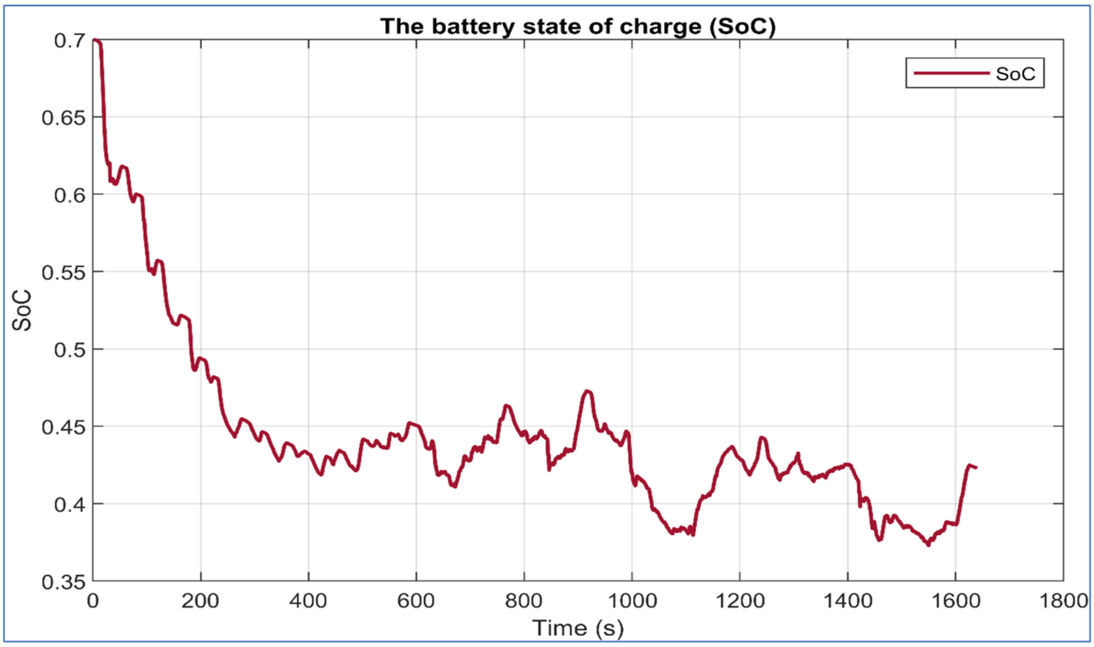

Figure IV.18: Soc for FEMO

The emission curves for the combustion engine in FEMO mode are shown in Figure IV.19:

- **Hydrocarbons (HC):** 0.168 g/km, indicating good combustion with a low quantity of unburnt residue.

- **Carbon monoxide (CO):** 1.165 g/km, with peaks at the start of the cycle before stabilizing thanks to better torque management.
- **Nitrogen oxides (NOx):** 0.199 g/km, slightly lower than conventional strategies.
- **Particulate Matter (PM):** 0 g/km, reflecting effective control of combustion and exhaust gas post-treatment.

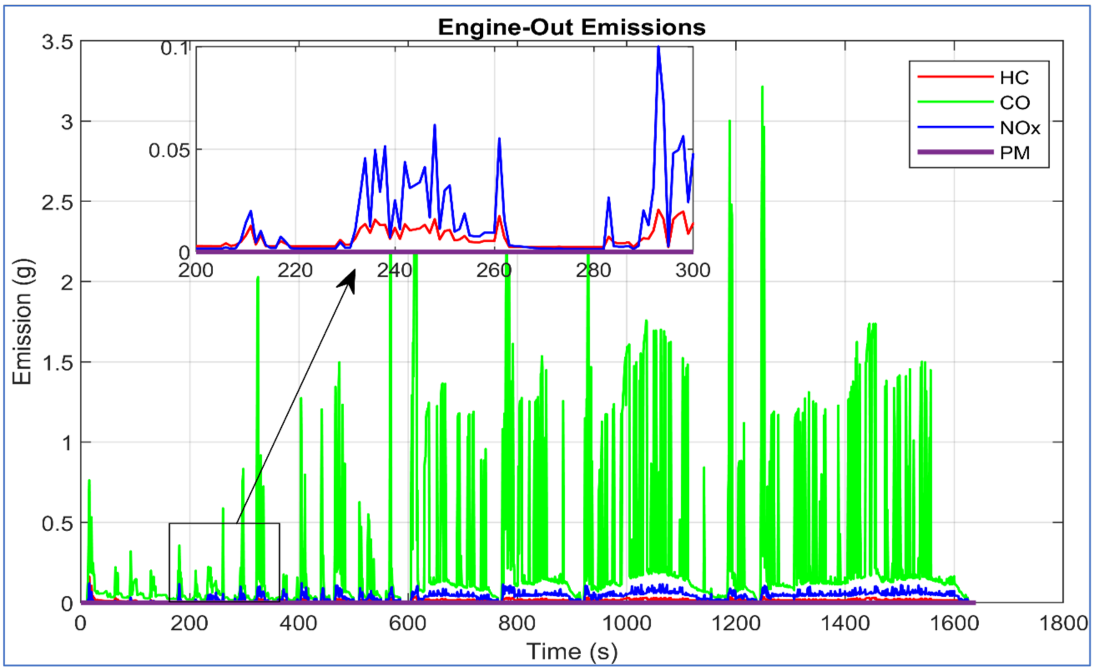

Figure IV.19: Engine-Out Emissions for FEMO

The FEMO strategy optimizes emissions management by keeping the combustion engine within efficient operating ranges, while exploiting the contribution of the electric motor to smooth out sudden variations in torque. This approach yields a substantial reduction in emissions compared to conventional strategies. Fuel consumption is estimated at 6.4 L/100 km, representing a balanced compromise between energy performance and limiting pollutant emissions.

Considering the lack of organization for controlling the torque converter and the varying modes of operation of the electric motor, which can cause fluctuations in the Non-directional Transmission Ratio (RTND), it is worth noting that the FEMO method is effective in managing emissions. At the same time, while the FEMO method ensures effective emission control, the gradual reduction of SoC highlights excessive consumption of electrical energy. Compensating for such losses through more efficient regenerative braking or external power could improve energy sustainability for longer cycles. Additionally, optimizing the transitions between the combustion engine and electric motor can provide better control over emission peaks observed during acceleration.

This case study demonstrates the effectiveness of the FEMO method in an urban environment, while also highlighting areas where energy management and emission control can be improved during prolonged driving conditions.

IV.7.3 Fuzzy Fuel Mode (FFM) Results

This analysis has demonstrated that the primary objective of the Fuzzy Fuel Mode (FFM) strategy is to minimize fuel consumption while preserving the dynamic performance required by the ARB02 cycle. Analysis of the results shows an optimized trade-off between energy efficiency, torque distribution, and system limits.

Figure IV.20 shows the evolution of the required torque, thermal torque, and electric torque. The required torque, as previously noted, varies during the cycle, with periods of acceleration and deceleration, both of which are characteristic of urban environments.

- Rapid and small-amplitude fluctuations, with a handful of variations between -100 and 150 N.m, are handled by the electric motor (EM).
- The thermal engine (ICE) reduces energy losses associated with inefficient regimes by operating in a more stable range of 0 to 80 N.m.

By limiting the excessive demands of the ICE, this redistribution enables the system to operate more efficiently, which helps to reduce fuel consumption.

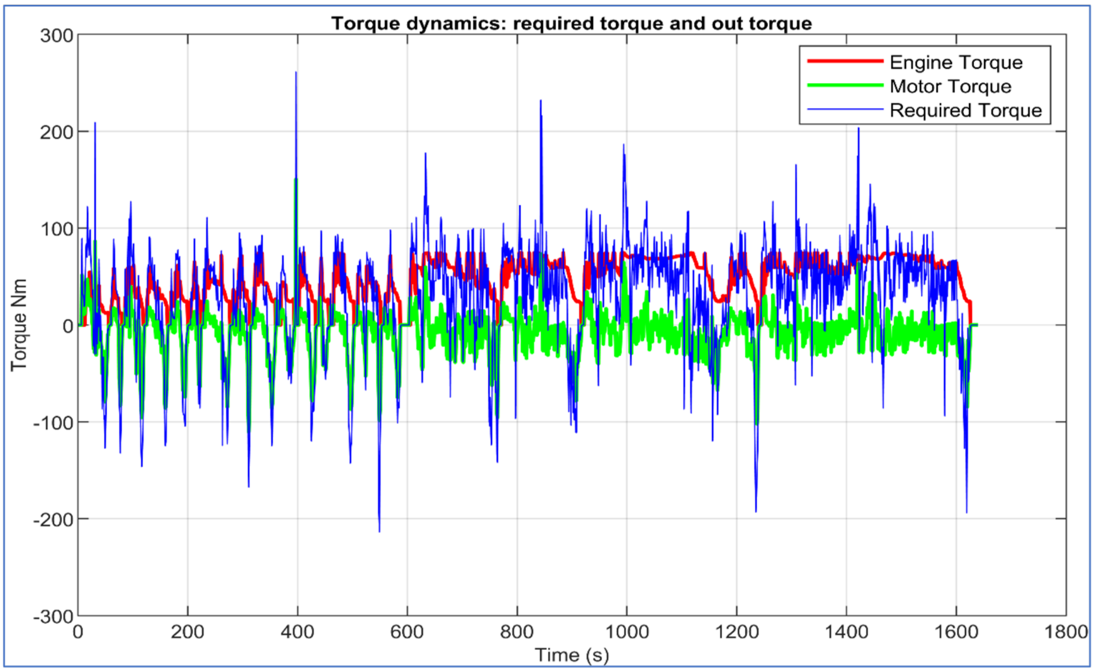

Figure IV.20: Torque Dynamics for FFM

Figure IV.21 illustrates the change in the battery's SoC throughout the cycle. The SoC gradually declines, evolving between 57% and 70%. This decrease translates into the use of electric motors to power internal combustion engines, resulting in lower fuel consumption. However, the ongoing SoC reduction highlights the need for improved energy recovery strategies using regenerative fuel, particularly during extended periods of deceleration.

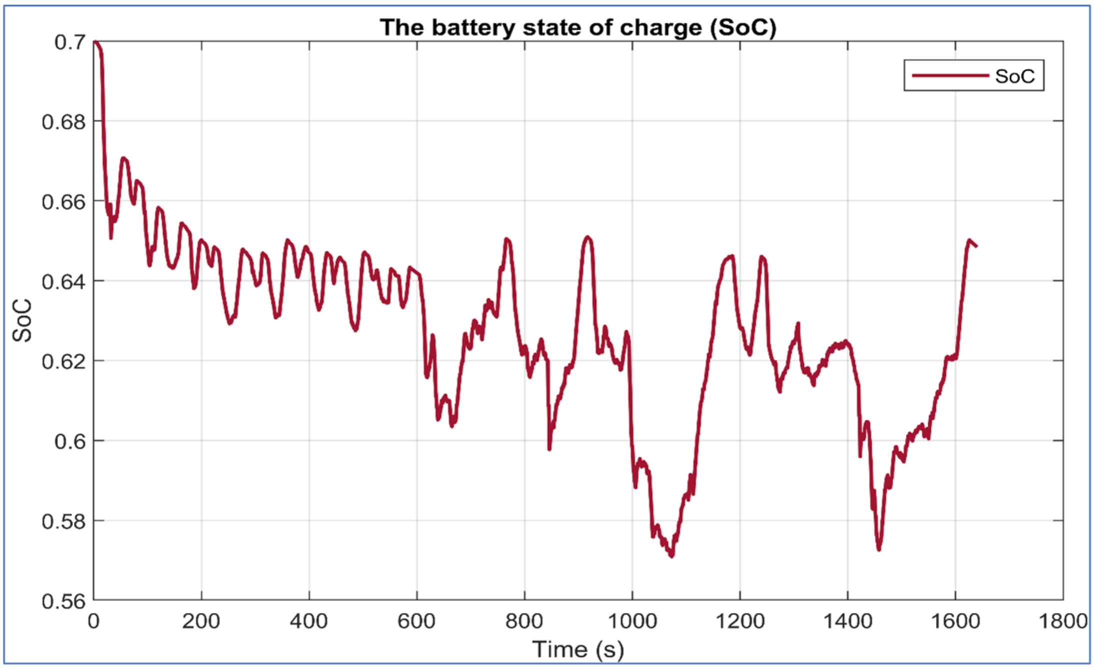

Figure IV.21: Soc for FFM

The emission profiles of the internal combustion engine under FFM are shown in Figure IV.22:

- **Hydrocarbons (HC):** 0.203 g/km, reflecting optimized combustion with reduced production of unburnt residues.
- **Carbon monoxide (CO):** 1.181 g/km, with slight increases during phases of high ICE load.
- **Nitrogen oxides (NOx):** 0.287 g/km, with localized peaks during rapid acceleration but reduced overall thanks to effective engine speed control.
- **PM (Particulate Matter):** 0 g/km, confirming clean combustion and reasonable control of exhaust gas after-treatment.

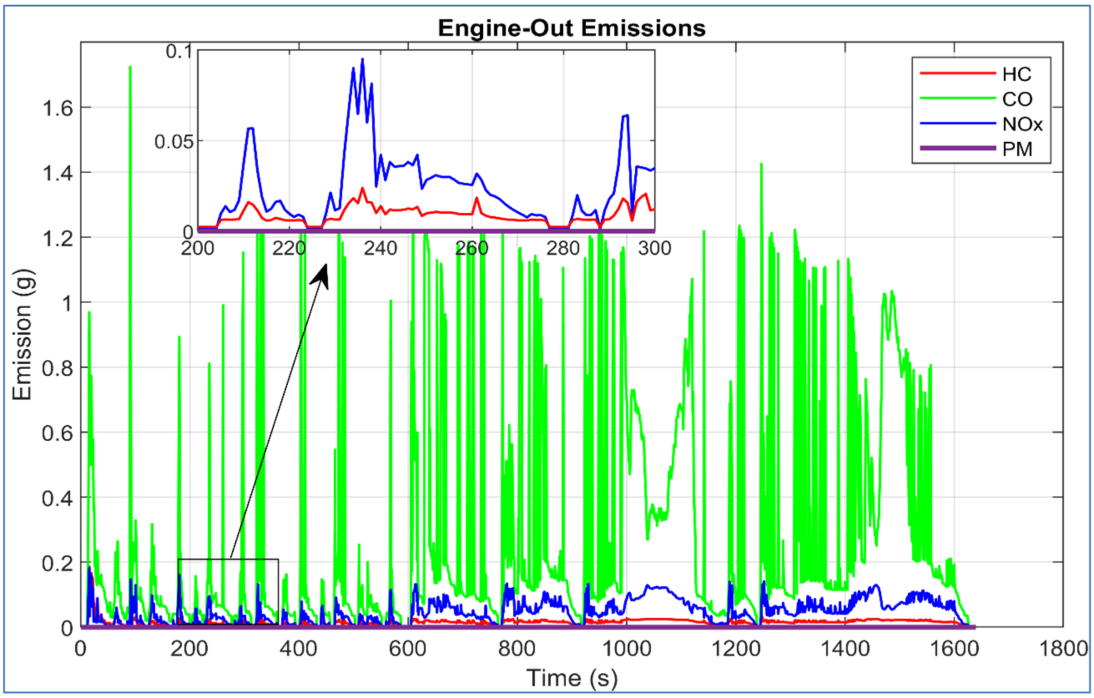

Figure IV.22: Engine-Out Emissions for FFM

While still meeting the requirements for the ARB02 cycle, the FFM strategy effectively reduces fuel consumption, which reaches 6.9 L/100 km. Optimizing the use of electromagnetic fields to absorb couple fluctuations also helps to reduce pollution emissions.

However, several improvement axes have been identified:

- Durability of the SoC: The battery's state of charge might be stabilized on longer cycles with a stronger regenerative battery and more effective management of the transitions between EM and ICE.
- Reduction of emission peaks: Additional measures might be implemented to prevent transitory increases in CO and NOx, especially during aggressive acceleration stages.

These results underline the potential of the FFM mode to meet the demands of modern driving cycles while reducing environmental impact.

IV.7.4 Fuzzy Logic-Based Control Strategy Results

The Fuzzy Logic-Based Control Strategy (FLCS) aims to optimize energy resource management in hybrid rechargeable vehicles (PHEVs) while reducing emissions and effectively meeting the demands of the ARB02 cycle. The results analysis reveals an equilibrium between energy efficiency, pair dynamics, and emission reduction. Figure IV.23 illustrates the evolution of the required torque, the engine torque ICE, and the electric motor torque throughout the cycle.

- The required torque varies between -50 and 250 N-m, characterizing the typical acceleration and deceleration phases.

- The EM provides 70% of the rapid adjustments, with fluctuations between -90 and 120 N-m, reducing the load on the ICE.
- The ICE operates in a more stable range, delivering a torque of between 10 and 80 N-m, thereby limiting the energy losses associated with variations in engine speed.

This optimizes powertrain efficiency by reducing fuel consumption and minimizing mechanical wear caused by abrupt transitions.

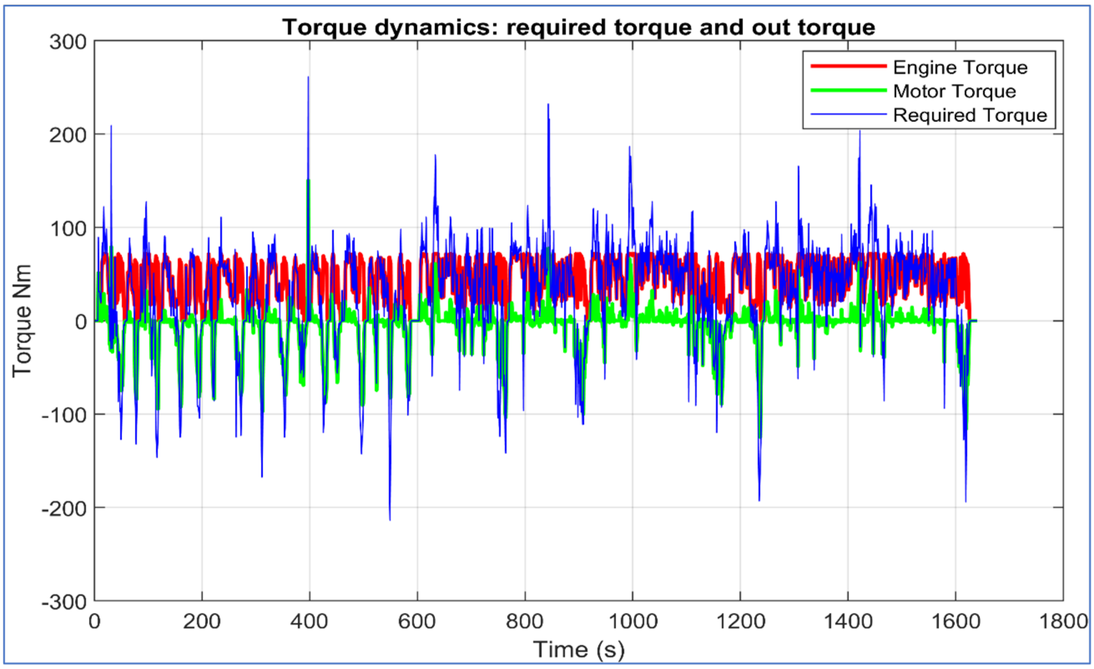

Figure IV.23: Torque Dynamics for FLCS

The evolution of SoC, as shown in Figure IV.24, exhibits a steady decline throughout the cycle, ranging from 70% to 35%. This decrease results in a high demand on the electrical motor to lower the ICE's thermal charge and restrict emissions. However, this trend highlights the need for regenerative brake optimization, especially during prolonged deceleration phases, to enhance the system's energy durability throughout extended cycles.

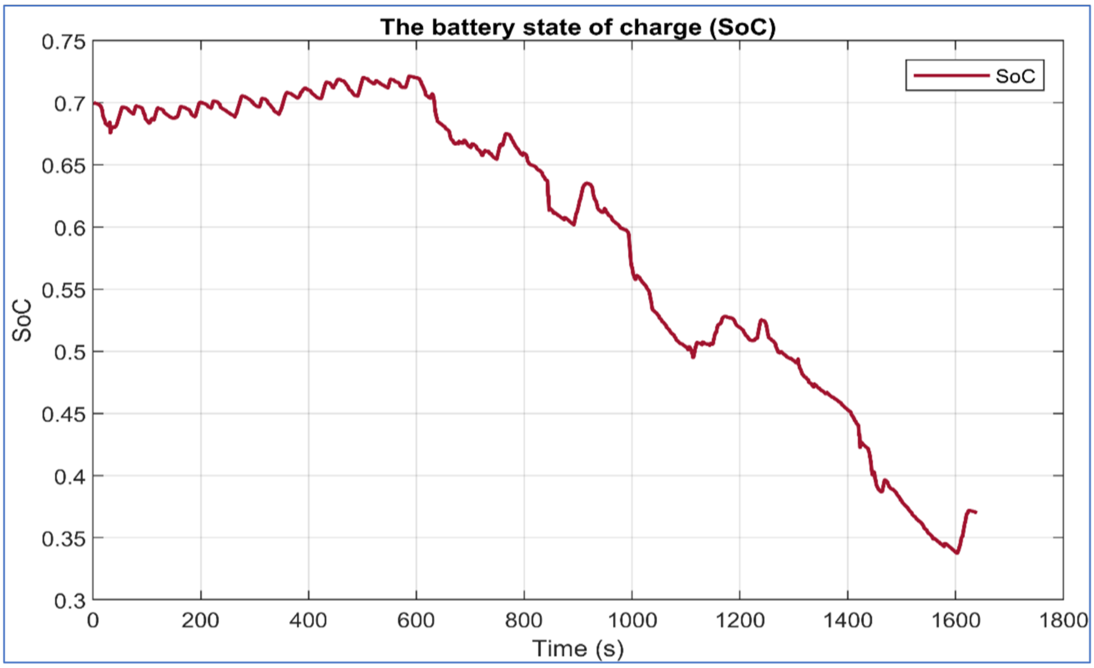

Figure IV.24: Soc for FLCS

Emission profiles, presented in Figure IV.25. Furthermore, although HC (0.019 g/km) and PM (0 g/km) emissions remain low, the peaks in CO and NOx observed during acceleration phases require particular attention. CO emissions reach 1.5 g/km before stabilizing at 0.9 g/km, while NOx emissions peak at 0.271 g/km. To mitigate these fluctuations, additional strategies could be implemented, including optimizing the anticipation of acceleration phases by pre-charging the electric motor. A revision of fuzzy control laws could also enable finer management of the alternation between energy sources, thereby reducing transient increases in pollutant emissions.

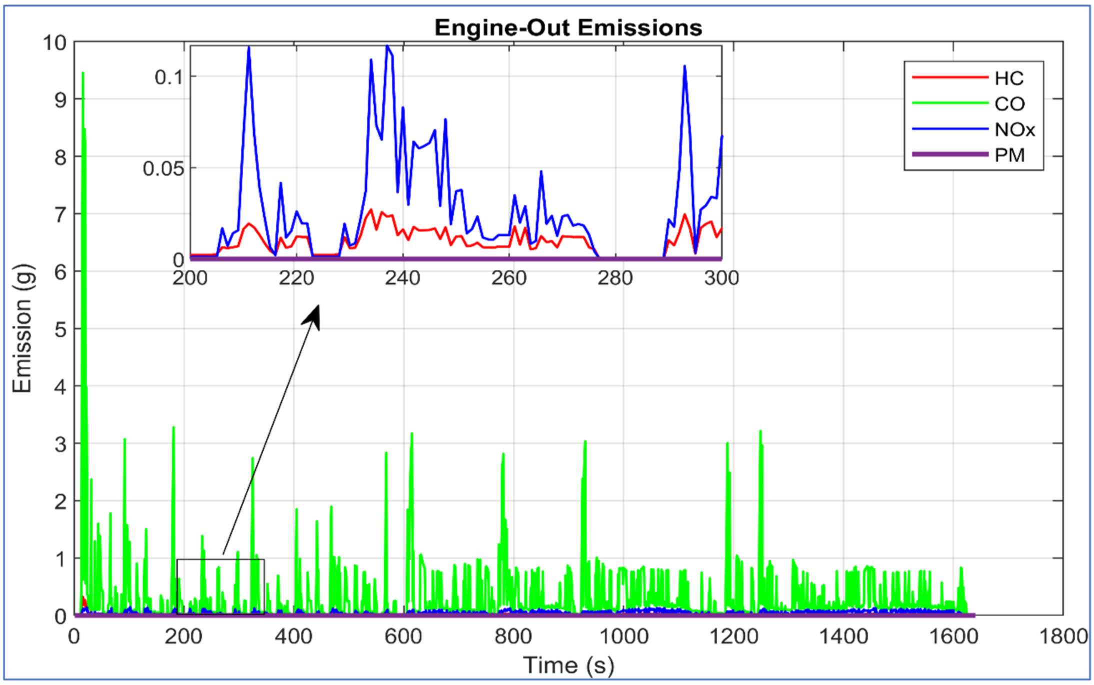

Figure IV.25: Engine-Out Emissions for FLCS

The FLCS strategy delivers a 4% reduction in fuel consumption compared with conventional management, with an average fuel consumption of 6.6 L/100 km. Adjusting the use of the EM and controlling the ICE to operate within its optimum efficiency range ensures an optimal compromise between fuel economy, Emission reduction, and dynamic response to cycle requirements.

Nevertheless, several areas of improvement were noted. The durability of the charging system could be improved with better application of regenerative braking and optimized transitions between ME and MCI to monitor battery charge status during extended cycles. In addition, strategies to reduce CO and NOx emission peaks, such as better prediction of acceleration phases with pre-charging the electric motor, are needed to mitigate transient increases in these pollutants.

These results confirm the potential of FLCS to meet the requirements of modern driving cycles while having a significant environmental impact.

IV.7.5 Optimization Algorithm for Enhancing Fuzzy Logic Results

In the next part, we use the genetic algorithm (GA), a solid and robust approach to deal with multi-objective optimization problems, in order to improve energy management methods based on fuzzy logic. The priority objectives were to reduce harmful emissions and fuel consumption. We also assessed how the variation in sample size and number of iterations influences calculation efficiency and quality of results.

The results show that a larger group size enables more efficient research in the field and provides better options to minimize fuel use and emissions. However, as there are more evaluations per iteration, larger groups require extended calculation times. While improving responses, the additional iterations also extend processing time. Smaller data sets and fewer iterations facilitate accelerated convergence, although they can also lead to sub-optimal solutions due to limited exploration.

These results underscore the importance of striking a balance between the number of iterations and the size of the set, tailored to operational requirements. If the main objective is to obtain quick solutions, then opting for smaller configurations may be more appropriate. However, complete optimization requires larger data sizes and more iterations. The genetic algorithm optimally solves fuzzy logic problems and can be adjusted to meet several objectives, such as reducing energy consumption and reducing environmental impact.

IV.7.5.1 Optimization for Fuel Consumption Reduction

This optimization, using a genetic algorithm, aims to enhance fuzzy logic-based control methods and reduce fuel consumption. The genetic algorithm was implemented in a pilot setting, with adjustments made to two critical parameters: the number of samples and the number of iterations. This experimental approach enabled a thorough examination of the impact of these adjustments on the quality of the obtained solutions. Following a careful iterative process, identifying the best-performing parameter combinations revealed significant fuel savings, associated with a balanced power distribution between the ICE and the EM.

The optimized membership functions for the fuzzy logic-based energy management system are shown in Figure IV.26 to Figure IV.29. The membership functions for the input variables, namely the battery SoC and the required torque (reqTorque), are shown in Figure IV.26 and Figure IV.27. Figure IV.28 represents the membership function for the output torque (outTorque), corresponding to the optimal system response. A three-dimensional representation of the optimized parameter surface is shown in Figure IV.29, which also shows how inputs and outputs interact after optimization. These findings demonstrate how genetic algorithm-based refinement significantly affects fuzzy logic membership functions, improving system performance and energy management.

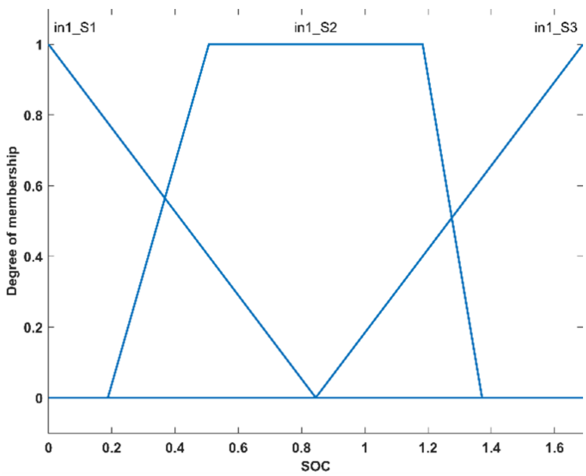

Figure IV.26: Optimized the EMS of the SOC parameter based on fuzzy logic.

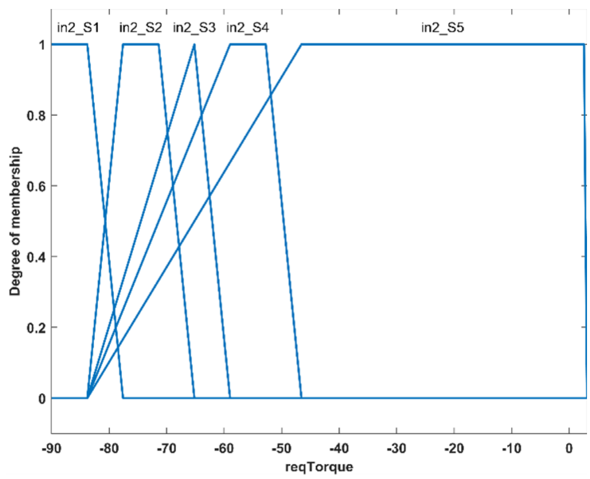

Figure IV.27: Optimized EMS of the req-Torque parameter based on fuzzy logic.

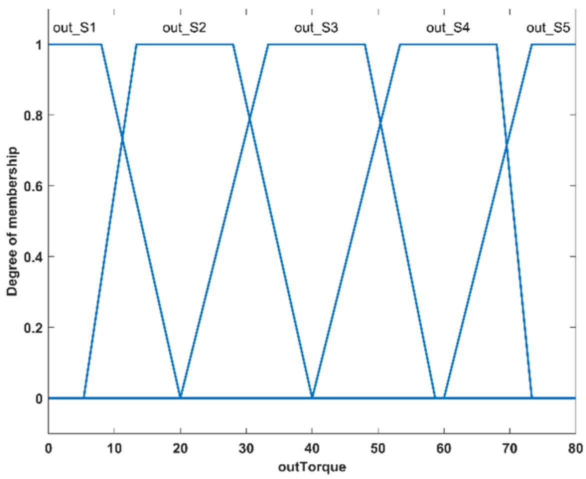

Figure IV.28: Optimized EMS of the out-Torque parameter based on fuzzy logic.

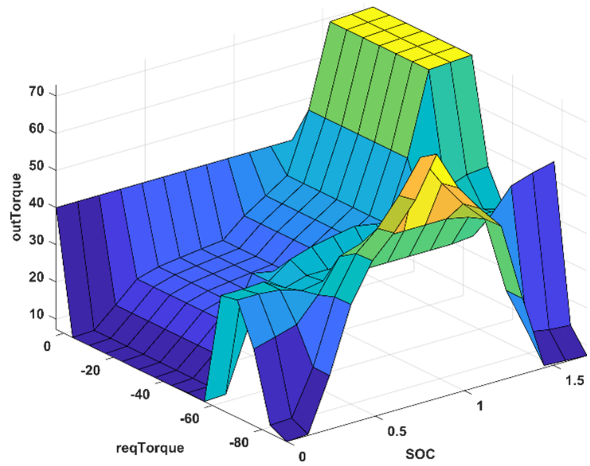

Figure IV.29: Surface of the EMS parameters using optimised fuzzy logic.

Figure IV.30 shows the evolution of the torque dynamics, including the needed torque (req_torque), the torque from the engine's internal combustion (ICE), and the electrical motor (EM) torque during the driving cycle.

- The required torque fluctuates between -200 Nm and 250 Nm, reflecting the acceleration and deceleration phases.
- The EM provides 70% of the rapid variations, with an operating range of -90 Nm to 150 Nm, reducing the load on the combustion engine.
- The ICE operates in a more stable range, between 0 Nm and 65 Nm, minimising energy losses associated with engine speed fluctuations.

Genetic algorithm optimization of the FLCS has improved powertrain efficiency by limiting engine torque variations and exploiting the EM to smooth transitions.

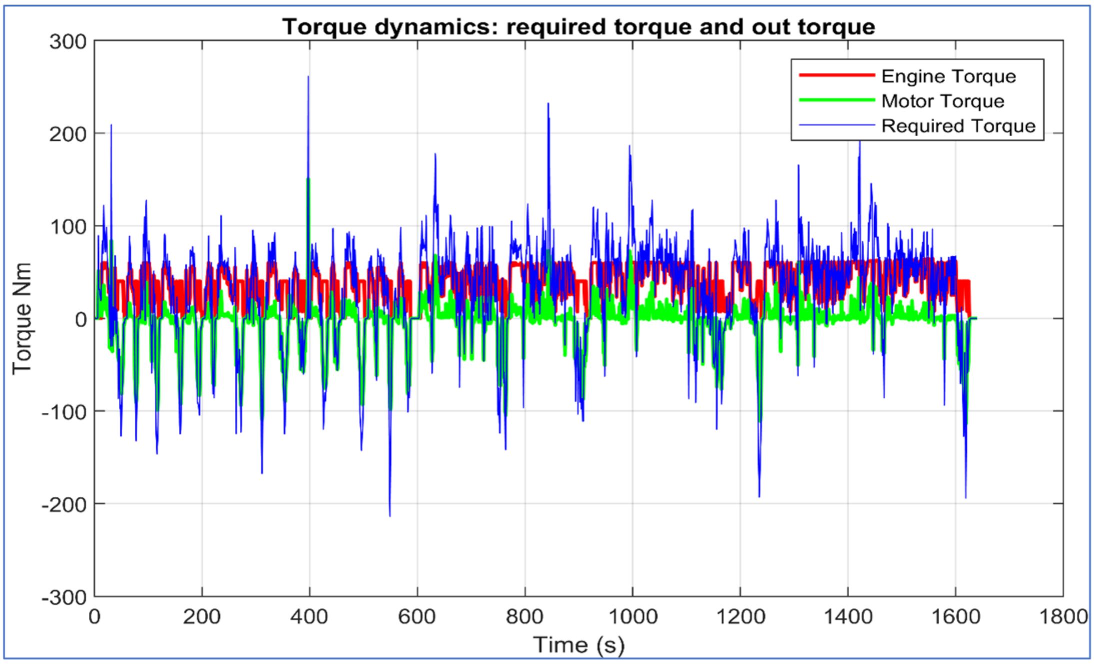

Figure IV.30: Torque Dynamics for Optimized FLCS

Figure IV.31 shows the trajectory of the SoC throughout the driving cycle. Optimized control has enabled a more efficient distribution of energy between sources, ensuring the optimal use of the battery.

- The state of charge gradually declines from 70% to 10%, indicating balanced energy consumption between the combustion engine and the electric motor.
- Better energy recovery is observed between 0s and 800s, limiting the rapid reduction in the SoC.
- Without an appropriate regenerative braking strategy, excessive discharge could compromise the vehicle's range.

By increasing the number of iterations and the size of the population in the optimization, it was possible to stabilize the SoC trajectory by improving the distribution of energy between the ICE and the EM.

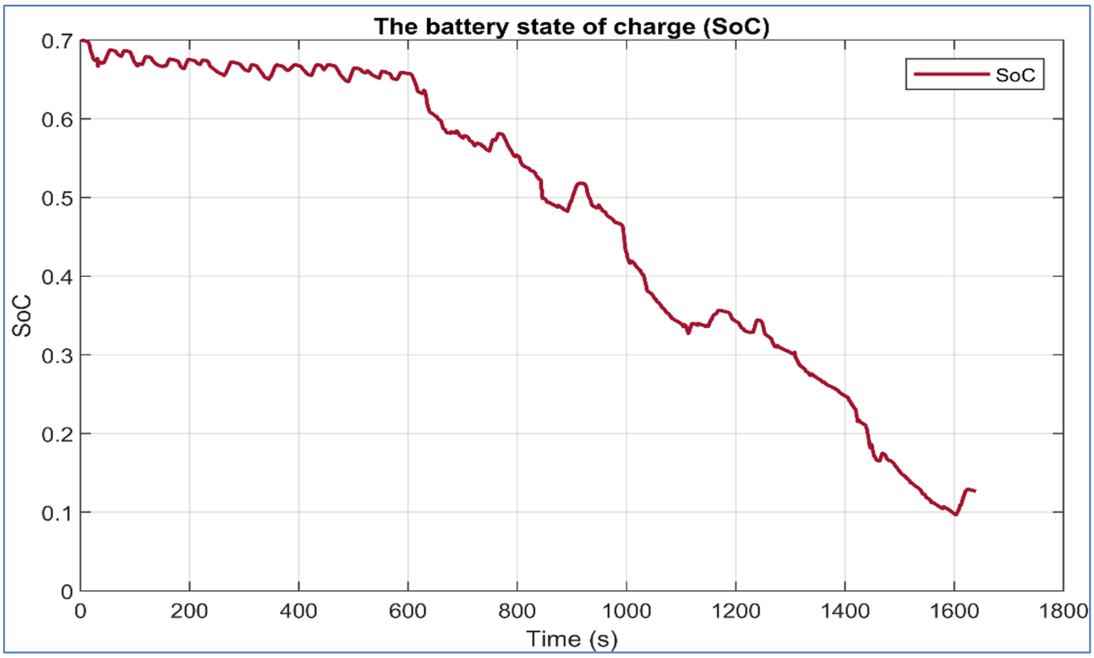

Figure IV.31: Soc for Optimized FLCS

Figure IV.32 shows the emissions of pollutants (HC, CO, NOx, and PM) over the driving cycle. By optimizing the FLCS strategy, it has been possible to limit peak emissions while maintaining optimum fuel efficiency.

- **HC and PM:** HC and PM emissions remain low, with average values of 0.019 g/km and 0 g/km, respectively, indicating well-controlled combustion.
- **CO:** CO emissions peak at 1.5 g/km during acceleration phases before stabilizing at 0.9 g/km, reflecting improved combustion efficiency thanks to optimized power distribution.
- **NOx:** NOx peaks at 0.271 g/km, mainly during dynamic transitions. However, optimization of the FLCS enables the reduction of these peaks by mitigating the severity of engine transients.

Optimization tests show that increasing the number of iterations and the size of the population contributes to better stabilization of emissions. However, these improvements result in higher computational costs. A future improvement could focus on the management of transitions between ICE and EM to attenuate NOx variations.

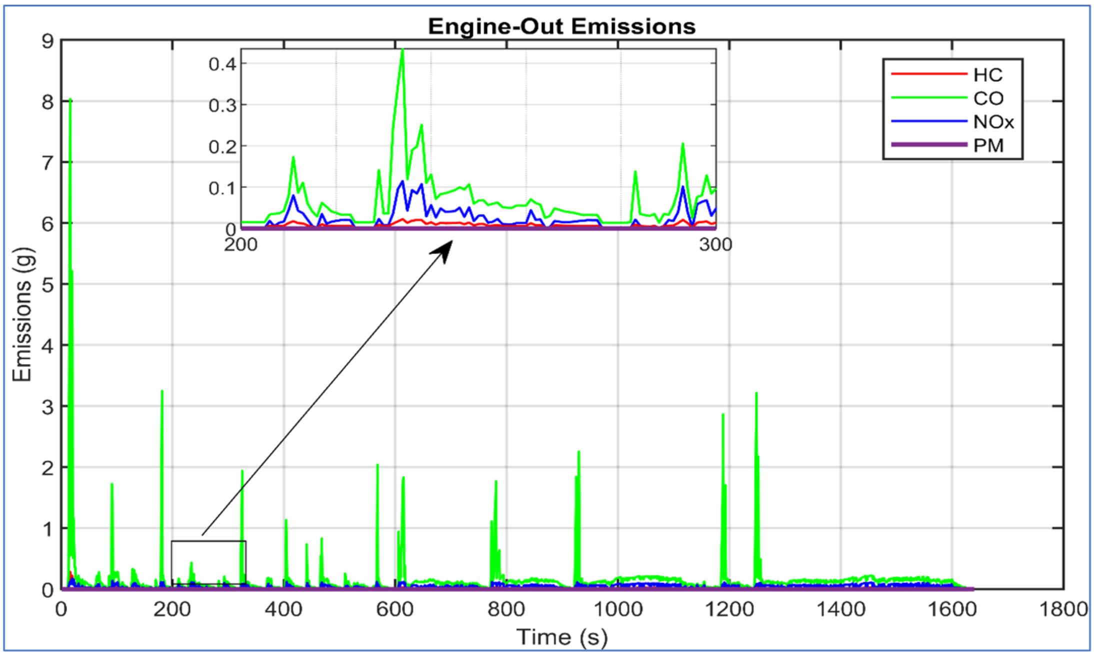

Figure IV.32: Engine Outlet Emissions for Optimized FLCS

The results confirm that optimizing the FLCS using a genetic algorithm significantly improves fuel economy, enhances torque management efficiency, and reduces emissions. The best configuration achieved a 14% reduction in fuel consumption, resulting in an average fuel consumption of 5.7 L/100 km. This optimization strikes a balance between fuel economy, emissions control, and dynamic response. Future improvements should focus on refining energy recovery strategies and further mitigating transient emissions for even greater optimization.

IV.7.5.2 Optimization for the Reduction of Pollutant Emissions

This optimization aims to reduce pollutant emissions (HC, CO, NOx, and PM) by maximizing the effectiveness of fuzzy strategies. Several simulations were carried out, varying the number of iterations and the size of the population in the genetic algorithm to explore different solutions. This experimental approach enabled configuration identification that effectively minimizes emissions while maintaining a good energy balance. Among the tests carried out, the most promising results, obtained from the best combinations of parameters, are presented and analyzed to illustrate the effectiveness of this optimization in reducing environmental impact.

The membership functions of the fuzzy logic-based energy management system's optimized parameters are shown in Figure IV.33 to Figure IV.36. More precisely, the membership functions of the input variablesthe battery (SOC) and the necessary torque (reqTorque)are displayed in Figure IV.33 and Figure IV.34, respectively. The output torque's (outTorque) membership function, which represents the system's optimal response, is seen in Figure IV.35. Lastly, Figure IV.36 shows the surface of the optimized parameters in three dimensions, giving a worldwide view of how the inputs and outputs of the system interact after optimization. These findings demonstrate how the genetic algorithm affects the membership functions' refinement, which enhances system performance and energy management.

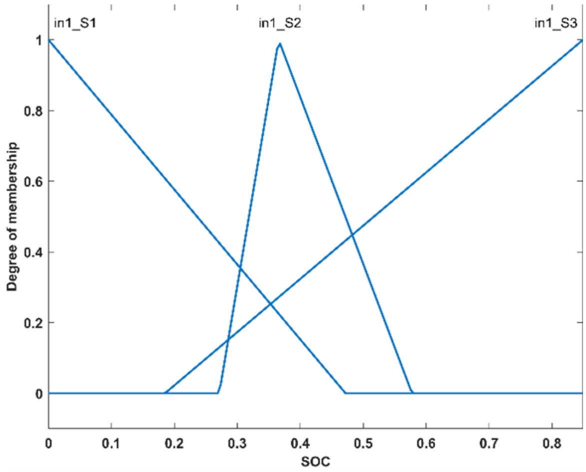

Figure IV.33: Optimized the EMS of the SOC parameter based on fuzzy logic.

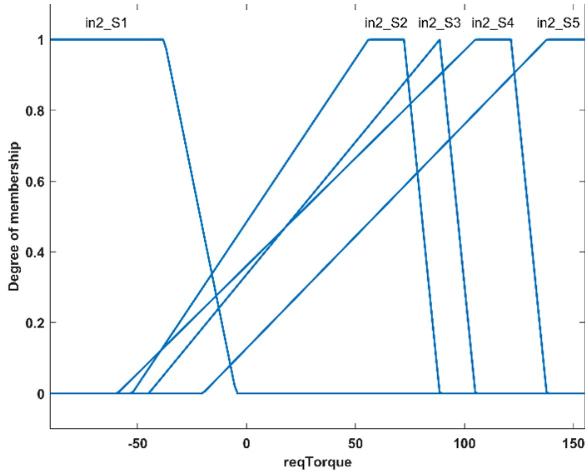

Figure IV.34: Optimized EMS of the reqTorque parameter based on fuzzy logic.

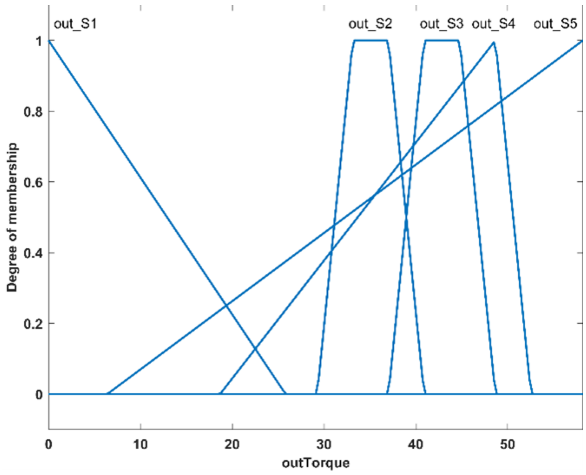

Figure IV.35: Optimized EMS of the outTorque parameter based on fuzzy logic.

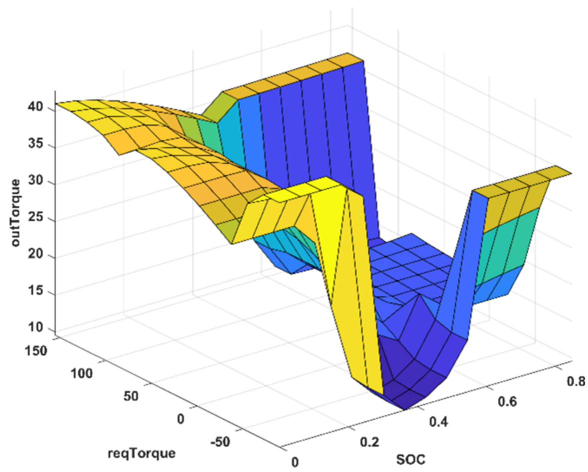

Figure IV.36: Surface of the EMS parameters using optimised fuzzy logic.

Figure IV.37shows the torque dynamics as a function of time, illustrating the torque split between the ICE and the electric motor. Optimization of the FLCS has resulted in improved power distribution:

- The average torque split is 35% ICE and 65% EM, reducing engine fluctuations and improving overall efficiency.
- The maximum torque required is 110 Nm, while engine torque varies between -100 Nm and 50 Nm, indicating effective energy recovery during braking phases.
- The reduction in sudden variations in ICE torque means fewer engine transients, reducing pollutant emissions and improving operating stability.

Optimization also limits excessive variations in engine torque and improves load distribution, resulting in more controlled fuel consumption and lower emissions.

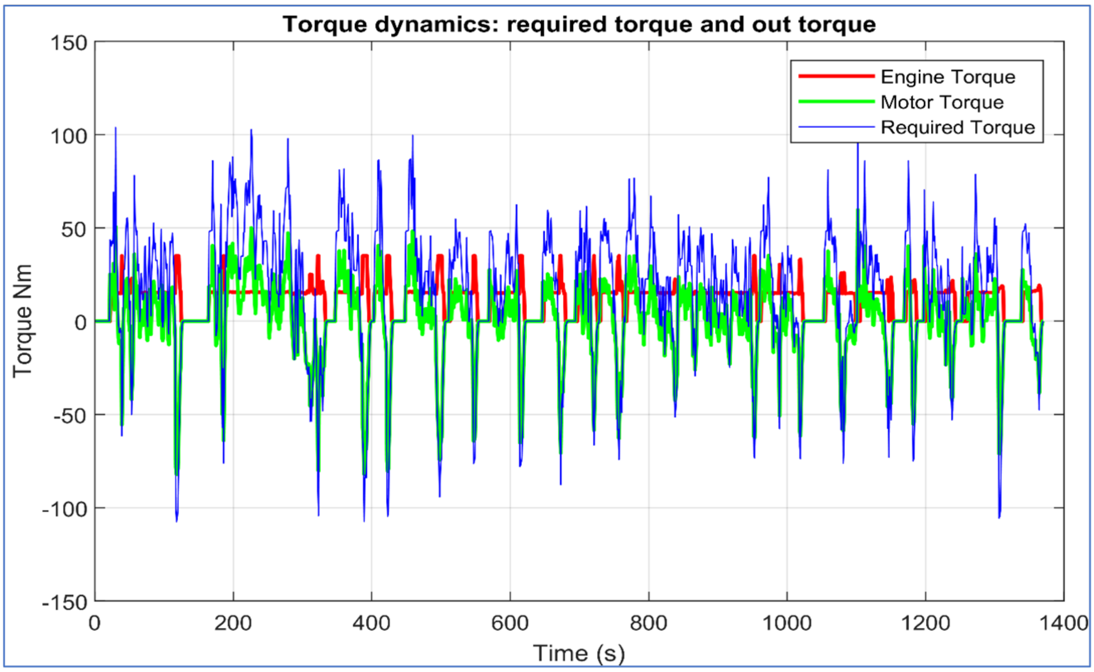

Figure IV.37: Torque Dynamics for Optimized FLCS (2)

The progression of the battery's charge level during the driving cycle is shown in Figure IV.38.

- The SoC decreases from 0.70 to 0.55 over a period of 1400 s, indicating balanced energy management between the battery and the combustion engine.
- The average discharge rate is around 0.000107%/s, guaranteeing extended vehicle range without premature depletion of energy reserves.
- Unlike conventional strategies, where the SoC drops rapidly below 0.50, the optimized strategy ensures a gradual decline, limiting over-reliance on the combustion engine and reducing fuel consumption.

The impact of regenerative braking is reflected in periods when the SoC curve stabilizes, although improvements could be made to recover more energy during deceleration phases.

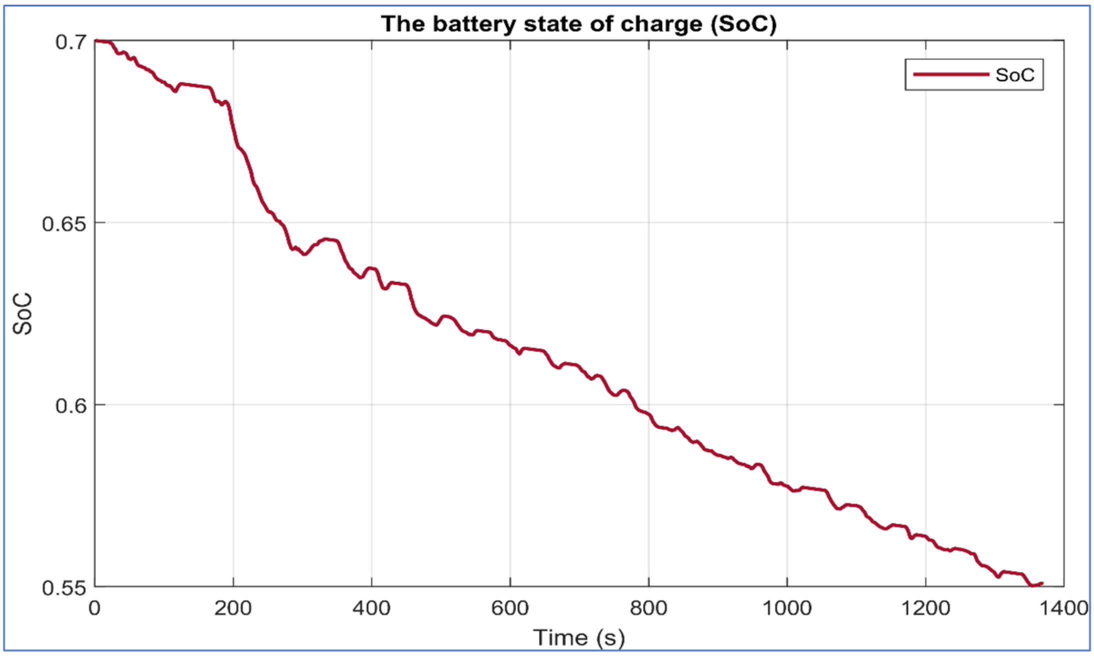

Figure IV.38: Soc for Optimized FLCS (2)

The emissions of HC, CO, NOx, and PM from the combustion engine are displayed in Figure IV.39.

- **HC:** Concentrations remain below 0.015 g/s, indicating more efficient combustion compared with non-optimized strategies.
- **CO:** The peaks observed during heavy acceleration reach 0.25 g/s, but the more efficient use of the electric motor during periods of high demand reduces average emissions by 18% compared with conventional strategies.
- **NOx:** The number of peaks has been reduced by 30%, maintaining an average concentration below 0.01 g/s thanks to more gradual torque transitions.
- **PM:** Fine particle emissions remain zero, confirming improved combustion stability.

Pollutant emissions are significantly decreased while maintaining effective energy management through FLCS optimization.

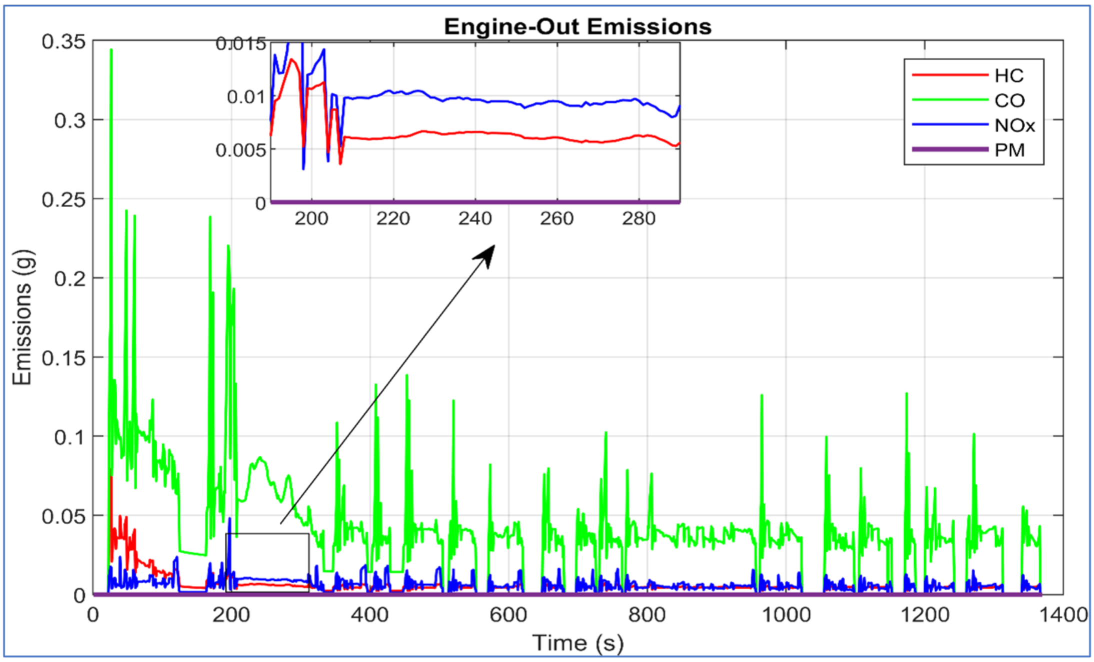

Figure IV.39: Engine Outlet Emissions for Optimized FLCS (2)

The optimized technique yields an efficient torque split (35% ICE, 65% EM), a stabilized SoC (from 0.70 to 0.55), and lower emissions (NOx: -30%, CO: -18%). These findings validate the FLCS's efficacy and present opportunities for improving the engine's thermal management and energy recovery.

Table IV.3: Summary table of energy management strategy performance

Fuzzy Logic Strategies	**Engine Torque (N.m)**	**Motor Torque (N.m)**	**SoC (%)**	**Fuel Cons (L/100 Km)**	**HC (g/ Km)**	**CO (g/ Km)**	**NOx (g/ Km)**	**PM (g/ Km)**
FEM	[0; 80]	[-90; 150]	[55-70]	6.6	0.215	1.107	0.299	0
FEMO	[0; 80]	[-100; 120]	[37-70]	6.4	0.168	1.165	0.199	0
FFM	[0; 80]	[-100; 150]	[57-70]	6.9	0.203	1.181	0.287	0
FLCS	[0; 75]	[-120; 150]	[34-70]	6.6	0.203	2.814	0.234	0
Fuel Consumption Reduction	[0; 65]	[-110; 150]	[10-70]	5.7	0.192	1.587	0.247	0
Reduction of Pollutant Emissions	[0; 40]	[-70; 50]	[55-70]	4.3	0.144	0.668	0.130	0

The results obtained from the different fuzzy logic strategies and their optimization by the genetic algorithm demonstrate significant improvements in energy management, fuel consumption, and emissions reduction. The summary table highlights the comparative performance of the different approaches, emphasizing the impact of the optimization process on the results.

Firstly, the torque split between the internal combustion engine and the electric motor varies according to the strategy adopted. Conventional fuzzy strategies such as FEM , FEMO , and FFM maintain a stable engine torque range (0 to 80 N.m). At the same time, the electric motor compensates for rapid variations in the load. The FLCS slightly restricts the combustion engine torque (0 to 75 N.m), allowing greater flexibility for the electric motor (-120 to 150 N.m). On the other hand, the optimization algorithm refines this balance by further reducing the engine's intervention. The optimized fuel consumption strategy reduces engine torque to 0-65 Nm, while the genetic algorithm-optimized emissions strategy limits torque to 0-40 Nm. This results in an 18.75% and 50% reduction in combustion engine use, respectively, compared to previous conventional fuzzy combustion strategies, reducing dependence on fuel and increasing dependence on the electric motor.

The variation in battery SoC further illustrates the impact of optimization. FLCS has a wide SoC range of 34%-70%, indicating significant battery utilization. FEM and FFM maintain a more conservative range (55%-70%), preserving battery charge. FEMO allows a slightly lower SoC range (37%-70%), reflecting greater reliance on the electric motor to reduce emissions. The fuel consumption optimization strategy exhibits the widest SoC range (10%-70%), demonstrating aggressive battery utilization to maximize fuel savings. This represents a 70.5% increase in SoC depletion compared to FLCS. Conversely, the emissions reduction strategy maintains a higher SoC (55%-70%), ensuring balanced electric energy use while minimizing emissions.

The impact of optimization is particularly evident in fuel consumption. Conventional fuzzy strategies (FEM, FEMO, FFM) consume between 6.4 and 6.9 L/100 km, with FEMO achieving the lowest consumption among them. FLCS offers no significant improvement, maintaining a consumption of 6.6 L/100 km. However, the optimized fuel consumption strategy reduces this to 5.7 L/100 km, marking a 10.9% reduction compared to FEMO and 17.4% compared to FFM. The emissions-optimized strategy achieves an even greater improvement, reducing fuel consumption to 4.3 L/100 km, a 32.8% reduction compared to FFM and a 33.6% reduction compared to FLCS.

The reduction in pollutant emissions is equally significant. The emissions-optimized strategy achieves the lowest levels, with HC reduced to 0.144 g/km (a 15.5% reduction compared to FEMO), CO reduced to 0.668 g/km (a 42.7% reduction compared to FEMO), and NOx reduced to 0.13 g/km (a 34.7% reduction compared to FEMO). The fuel consumption-optimized strategy also improves emissions performance compared to conventional fuzzy strategies, though not as drastically as the emissions-focused optimization. However, compared to FLCS, which exhibits the highest NOx emissions (2.814 g/km), the optimized emissions strategy achieves a 95.4% reduction in NOx emissions, highlighting the inefficiency of non-optimized fuzzy strategies in controlling peak pollutants.

These results highlight several key insights. Firstly, there is an inherent trade-off between reducing fuel consumption and reducing emissions. While minimizing fuel consumption achieves significant savings, emissions-focused optimization ensures minimal pollution levels, albeit with stricter constraints on combustion engine usage. Secondly, efficient power management allows a precise balance between the combustion engine and the electric motor, ensuring efficient power distribution. Finally, optimisation improves the dynamic management of battery charge, avoiding excessive discharge, which, when repeated, damages the battery and reduces its lifespan, while maximising the use of electrical energy compared to other energies. These data demonstrate that optimisation algorithms bring significant improvements in energy management in hybrid vehicles, reducing fuel consumption and environmental impact by significantly reducing emissions.

IV.8 Conclusion

This chapter has presented a comprehensive review of fuzzy logic-based energy management strategies for parallel hybrid electric vehicles, demonstrating their significant potential to enhance fuel efficiency and reduce emissions. The comparative analysis of five fuzzy control strategies, including a genetic algorithm-optimized approach, verified the effectiveness of adaptive, intelligent control in optimizing power distribution between the internal combustion engine and electric motor. These strategies improve battery state-of-charge management and reduce fuel consumption and pollutant emissions substantially under simulated driving conditions.

While the simulation results are promising, further validation through real-world testing is essential to address variability in driving conditions and battery performance. Additionally, future research should focus on developing dynamic, self-learning fuzzy controllers and multi-objective optimization frameworks to better balance efficiency, emissions, and battery longevity. Expanding this research to more complex hybrid architectures and integrating novel energy storage technologies will be crucial for advancing next-generation hybrid propulsion systems.

Ultimately, this work lays essential groundwork for the practical application of intelligent control and optimization techniques aimed at improving the sustainability and performance of hybrid and electric vehicles, bridging the gap between theoretical development and real-world automotive solutions.

Chapter V

Remote Monitoring of Electric Vehicle Batteries

V.1 Introduction

This chapter presents an in-depth examination of remote monitoring for electric vehicle (EV) batteries. The rise of electric vehicles is crucial in reducing environmental pollution and decreasing reliance on fossil fuels, but challenges remain in extending battery life and lowering maintenance costs.

Central to this chapter is the monitoring of vital battery parametersspecifically, the State of Charge (SOC), battery temperature, battery current, and battery voltage. The SOC shows the remaining battery capacity, which is essential for managing charge cycles and avoiding damage from overcharging or deep discharging. Monitoring battery temperature ensures thermal conditions stay within an optimal range, preventing heat-related degradation and performance issues. Additionally, tracking battery current and voltage provides critical insights into the battery's operational state. It helps detect abnormal behaviors that could affect performance and safety. Maintaining these parameters within recommended limits is essential because extreme states can significantly lower battery efficiency and lifespan.

In this chapter, multiple driving cycleshighway, urban, and mixedwere used to evaluate battery and vehicle performance under diverse conditions. Battery data (SOC, current, voltage, and temperature) were continuously recorded to analyze energy consumption, efficiency, and thermal behavior. An unsupervised K-means clustering approach was first applied to group the data into three operational states (Normal, Elevated, Critical), using SOC and temperature as the leading indicators due to their critical role in energy availability and safety. These clusters then served as labels for a supervised Random Forest classification, which incorporated all four parameters to enhance predictive accuracy. This two-step methodology enabled reliable categorization of battery states, providing insights into energy demand, thermal stress, and state-of-health, thereby supporting the validation of hybrid energy management strategies under dynamic driving conditions.

V.2 Importance of Battery Monitoring in Electric Vehicles

Electric vehicle batteries are fundamental to the vehicle's operational performance, driving range, and overall lifespan. The battery pack represents one of the most critical and costly components in EVs, and its proper management is crucial for maximizing vehicle reliability and efficiency. Maintaining battery health requires continuous monitoring due to several inherent challenges related to battery degradation, thermal management, and capacity loss. Battery degradation occurs progressively through chemical aging processes accelerated by factors such as high charge/discharge rates, deep cycles, and exposure to extreme temperatures. These factors contribute to reduced capacity and increased internal resistance, which diminish battery performance and reduce the achievable driving range.

One of the main technical challenges is the thermal stability of lithium-ion batteries, commonly used in EVs. Batteries operate optimally within a tight temperature range, generally between 20 °C and 30 °C. Elevated temperatures accelerate side reactions inside the battery cells, promoting rapid aging and posing safety risks, including thermal runaway. Conversely, cold temperatures reduce battery capacity and power output, impairing vehicle performance. Effective battery thermal management and real-time temperature monitoring can prevent these detrimental effects, helping to maintain optimal operating conditions and prolong battery life.

Furthermore, accurate monitoring systems enable the detection of abnormal behaviors early, such as overheating, voltage irregularities, or current spikes that could indicate faults or potential failures. Through these systems, predictive maintenance becomes possible, allowing timely interventions that reduce unplanned downtime and maintenance costs. In addition to economic benefits, battery monitoring enhances safety by preventing hazardous situations, such as overcharging or deep discharging, which can cause irreversible battery damage or fire hazards. Overall, the integration of advanced battery monitoring contributes significantly to extending battery lifespan, improving EV reliability, and supporting the broader adoption of clean transportation solutions.

V.3 Key Battery Parameters for Monitoring

V.3.1 State of Charge (SOC)

The State of Charge (SOC) represents the remaining usable capacity of an electric vehicle battery expressed as a percentage of its total capacity. It is a fundamental metric for energy management and trip planning, acting as an indicator of how much energy the battery can still deliver before recharging is necessary. Maintaining SOC within an optimal range, usually between 20% and 80%, minimizes battery wear by preventing stress induced by full charges or deep discharges, both of which accelerate degradation mechanisms such as lithium plating and electrolyte breakdown. Accurate SOC estimation is crucial not only for preserving battery health but also for optimizing charge control strategies and enhancing regenerative braking efficiency, thereby improving overall vehicle performance and energy utilization.

Recent advancements in real-time SOC monitoring leverage dynamic impedance spectroscopy, enabling the estimation of battery state during operation without the need for resting states. This technique captures detailed internal battery characteristics and supports predictive maintenance by forecasting the battery cell's potential lifespan and detecting early signs of deterioration. Such improvements in SOC estimation algorithms are critical to the development of intelligent Battery Management Systems (BMS) and cloud-based platforms that allow continuous remote monitoring of EV battery health.

V.3.2 Battery Temperature

Battery temperature directly affects the efficiency, safety, and longevity of lithium-ion batteries used in EVs. The optimal operating temperature range is generally between 20 °C and 30 °C; deviations from this window can lead to significant adverse effects. Elevated temperatures accelerate electrochemical side reactions inside the battery cells, which not only degrade materials faster but also raise the risk of thermal runawaya dangerous and potentially catastrophic event. Conversely, low temperatures slow chemical reactions, reducing battery capacity and hampering the ability to accept charge during cold starts, resulting in decreased vehicle range and performance.

Onboard thermal management systems employ temperature sensors and active cooling or heating elements to maintain battery temperature within safe limits. These systems rely on continuous temperature monitoring to dynamically adjust thermal control mechanisms, thereby optimizing battery life and operational safety.

V.3.3 Battery Current and Voltage

Battery current represents the flow of electric charge during charge and discharge cycles and provides essential insights into power consumption and battery load conditions. Voltage monitoring across cells or modules detects imbalances and early warning signs of degradation, such as increased internal resistance or capacity loss. Together, current and voltage measurements allow the BMS to implement critical protective functions, including overcurrent protection, voltage balancing, and fault detection, which prevent damage from electrical stress and ensure optimal performance.

Through continuous monitoring of these electrical parameters within manufacturer-specified limits, the BMS can safeguard battery health, extend lifespan, and secure safe EV operation over time.

V.4 Real-time battery monitoring with AI algorithms

The real-time simulation of a reference model, named ASM, was conducted using the Scalexio platform from dSPACE. This model represents a parallel hybrid electric vehicle architecture. The study involved conducting tests across multiple driving cycles, including highway and urban scenarios, to evaluate battery performance under varying conditions. Data regarding the battery's behavior were collected and analyzed for each scenario, providing insights into the energy management and efficiency of the hybrid system throughout different driving environments. This approach enables comprehensive evaluation of the vehicle's dynamic responses and energy storage characteristics in real-time operation.

The ScaleXIO platform developed by dSPACE is a widely used real-time hardware solution for Hardware-in-the-Loop (HIL) simulation and testing. It enables the connection of a real electronic control unit (ECU) to a virtual environment, allowing the evaluation of its behavior under realistic conditions. When combined with the ASM Vehicle Dynamics package, it provides a comprehensive and realistic model of vehicle dynamics, encompassing chassis, tires, steering, suspension, transmission, braking, and interaction with the road environment. The modeling is based on a multibody approach considering degrees of freedom of the chassis, axles, and nonlinear suspensions. Tire models include recognized formulations such as the Magic Formula or TMEasy, capable of simulating longitudinal and lateral slip, dynamic radius, camber angle, and contact forces. Steering is represented by a realistic rack-and-pinion model, with or without assistance, also reproducing the steering feedback felt at the wheel.

The ASM model incorporates detailed subsystems such as the engine, drivetrain, vehicle dynamics, and environment, all coordinated with the control implemented in the soft ECU. The fundamental architecture and signal flow of the ASM model used in the simulation are illustrated in Figure V.1, showing interactions among the ECU, engine, drivetrain, vehicle dynamics, and environment [1].

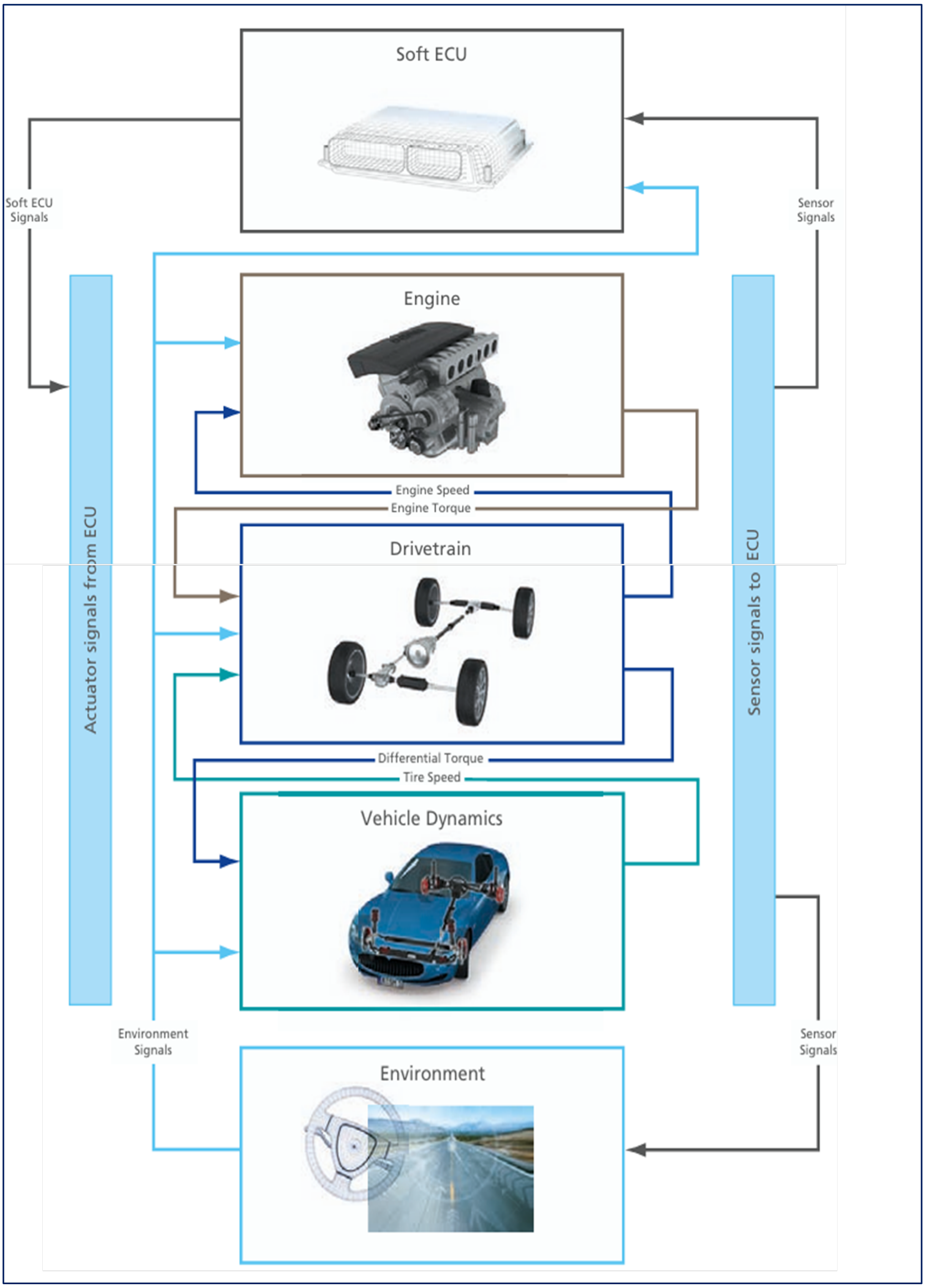

Figure V.1: ASM model architecture and signal flow between the Soft ECU, Engine, Drivetrain, Vehicle Dynamics, and Environment [1].

The transmission system is modeled in detail, including the engine, clutch, manual or automatic gearboxes, differential, all-wheel drive, and flexible shafts. Braking systems are described by a comprehensive hydraulic model comprising master cylinder, circuits, valves, and disc or drum brakes, with optional pneumatic system modeling for heavy commercial vehicles. This approach enables the simulation of critical functions such as ABS, ESP, or traction control.

This detailed modeling of the vehicle subsystems is visually represented in Figure V.2, highlighting the engine, transmission, steering, brakes, suspension, and tires of the ASM vehicle.

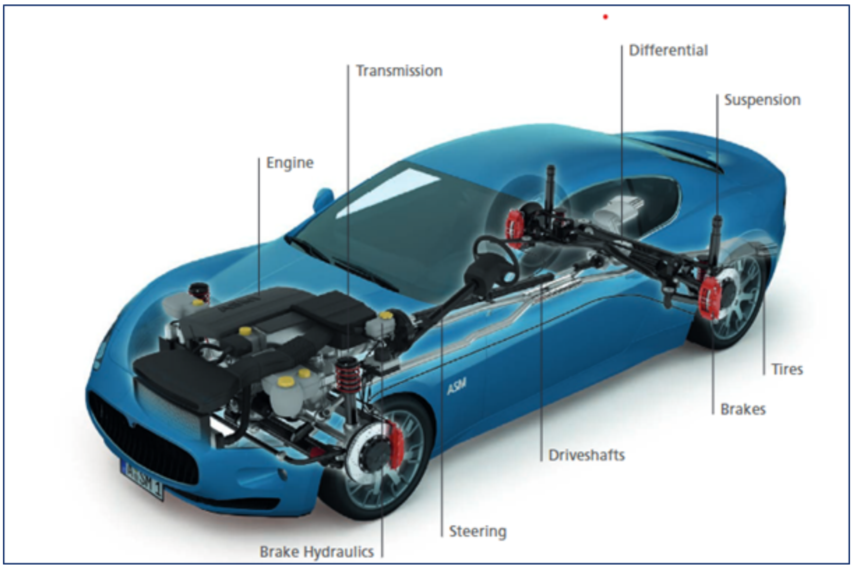

Figure V.2: Detailed 3D representation of ASM vehicle subsystems, including engine, transmission, brakes, steering, suspension, and tires [1].

The road environment is highly flexible: users can create straight or curved roads, define slope profiles, and assign different adhesion conditions such as dry, wet, or icy surfaces. Standard maneuvers like lane changes, emergency braking, or tight turns are directly available, facilitating the validation of driver assistance and active safety systems.

To parameterize the models and visualize results, dSPACE provides two complementary tools: ModelDesk, allowing vehicle, road, and maneuver configuration through an intuitive graphical interface, and MotionDesk, offering real-time 3D visualization of simulations.

The ModelDesk interface used for setting up vehicle parameters, defining road conditions, and designing maneuvers is shown in Figure V.3, illustrating the user-friendly graphical environment provided by dSPACE.

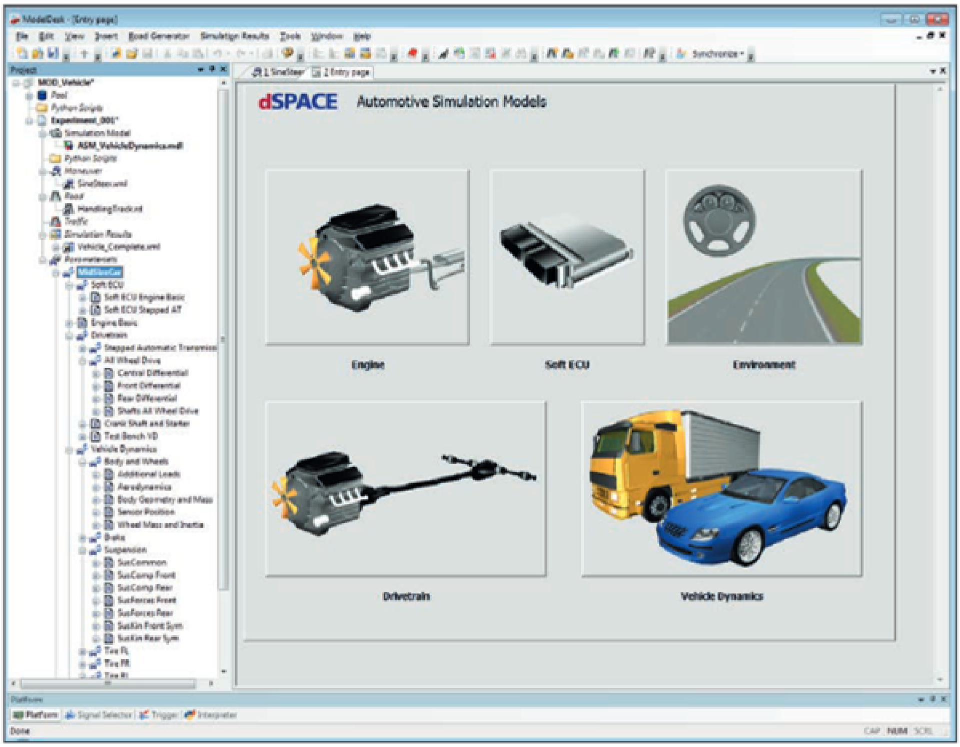

Figure V.3: ModelDesk graphical user interface for configuration of vehicle models, road scenarios, and maneuvers in dSPACE [1].

The combined use of ScaleXIO and ASM Vehicle Dynamics offers several key advantages. Firstly, it enables realistic HIL testing where the ECU is subjected to virtual but representative driving conditions without the need for expensive physical prototypes. Secondly, it significantly reduces development time and costs, as virtual testing can be carried out early in the design cycle. Additionally, the models are open and modifiable in Simulink, offering flexibility to adapt to various vehicle types ranging from small city cars to trucks or trailers. Lastly, continuity is ensured between offline and real-time simulation since the same models can be used both for theoretical studies and hardware tests with ScaleXIO.

In this work, multiple driving cycles were employed to evaluate the battery and vehicle performance across different usage scenarios. These cycles encompass standardized highway driving profiles, urban stop-and-go traffic, and mixed conditions, covering a wide range of operational modes. Battery data, including state of charge, current, voltage, and temperature, were continuously recorded during these cycles, enabling detailed analysis of energy consumption, efficiency, and thermal behavior in real-world, representative scenarios. This comprehensive dataset supports the validation of the hybrid energy management strategies under dynamic and varying driving conditions.

To further analyze the recorded battery data, an initial unsupervised clustering approach was employed using the K-means algorithm. This choice was motivated by the nature of the problem, as the dataset (Battery.mat) initially contained no predefined classes or labels. K-means served as an exploratory step to automatically partition the data into distinct groups, specifically three clusters, based primarily on key physical indicators: state of charge (SOC) and battery temperature (Tbat). These two variables were selected due to their critical technical and physical significance. SOC reflects the remaining energy in the battery, with low SOC levels indicating potentially critical states, such as deep discharge risk. Temperature directly impacts battery safety and lifespan; elevated temperatures can cause accelerated degradation or thermal risks. Although voltage (Vbat) and current (Ibat) exhibit significant short-term variability linked to driving dynamics, they were less suitable alone for initial labeling due to their transient nature.

The clusters identified from K-means thus provided automatic labels representing operational statescommonly categorized as Normal, Elevated, or Criticalbased on SOC and temperature thresholds, which align with robust physical understanding. Following this unsupervised step, a supervised classification was performed using the Random Forest algorithm, chosen for its robustness, ability to handle nonlinear relationships, and effectiveness in managing multivariate datasets [50]. The Random Forest model was trained on these labeled data, utilizing all four key battery parameterscurrent (Ibat), voltage (Vbat), SOC, and temperature (Tbat)as input features. In this context, voltage and current serve as complementary predictive variables that capture real-time load and energy flow dynamics, enriching the model's capacity to distinguish between battery operational states beyond solely SOC and temperature indicators.

The objective of applying Random Forest in this two-step approachfirst clustering, then supervised learningwas to categorize battery states under varying driving cycles and conditions. This methodology enables the identification of patterns associated with energy demand, thermal stress, and state-of-health indicators. Such data-driven classification provides valuable insights for developing and validating hybrid energy management strategies, ultimately improving battery performance and reliability across diverse real-world scenarios.

V.5 Evaluation of AI-based battery monitoring

V.5.1 FTP-75 Drive Cycle

The FTP-75 (Federal Test Procedure) is a standard U.S. urban driving test cycle used for vehicle emission certification and fuel economy testing Figure V.4. It lasts 2500 seconds (about 43 minutes) with a total distance of about 23.66 km. It consists of three phases: a cold start transient phase, a stabilized phase, and a hot start transient phase after the engine is stopped for 10 minutes. The average speed is about 34.1 km/h, with a maximum speed of 91.3 km/h. The cycle simulates city driving with frequent stops and accelerations. Typical speed-time profile: speeds vary between 0 and 91.3 km/h with distinct cold and hot start phases.

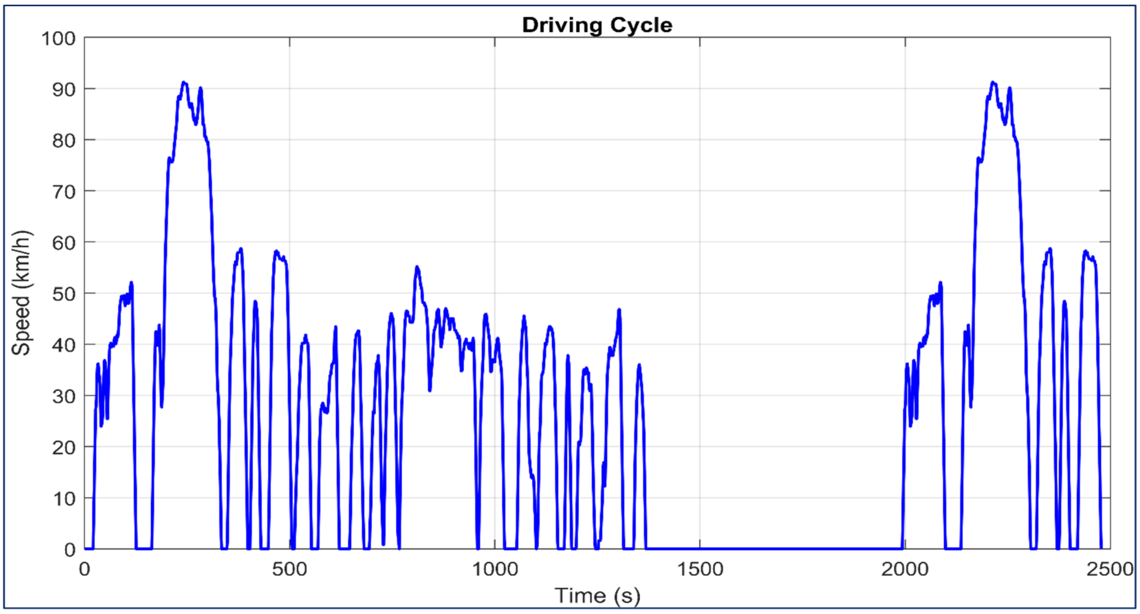

Figure V.4: FTP-75 Drive Cycle

The experimental dataset was extracted from the standardized driving cycle, FTP75. The recorded signals include the battery voltage (Vbat), current (Ibat), state of charge (SOC), and temperature (Tbat). These parameters constitute the fundamental basis for the analysis and subsequent classification process, as they capture both the electrochemical and thermal dynamics of the battery during representative operating conditions.

Before applying any machine learning technique, the raw signals (Figure V.5) were visualized to provide an overview of the battery behavior throughout the driving cycles. The time-series plots of voltage, current, SOC, and temperature allow a preliminary inspection of the data quality and highlight the expected variations. For example, SOC decreases progressively during the discharge phases, while the current exhibits significant fluctuations during acceleration and deceleration events. The temperature shows slower variations, but it plays a crucial role in assessing the health and safety of the battery.

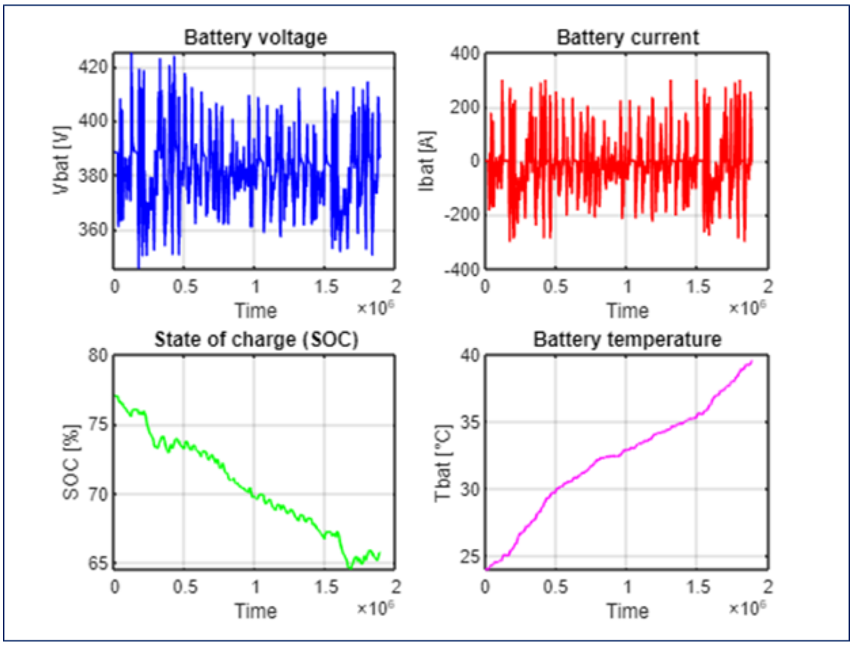

Figure V.5: Signals' raw visualizations.

The four measured signals were organized into a feature matrix for machine learning purposes. To ensure fair comparison among features with different scales, the dataset was normalized using the z-score method. Normalization prevents features with large numerical ranges (such as voltage) from dominating the learning algorithm, thus allowing SOC, current, and temperature to contribute equally to the classification process.

Unsupervised clustering was first performed using the K-means algorithm with k = 3, aiming to partition the dataset into three distinct operating states. This choice corresponds to a natural division of battery conditions into three categories: normal, elevated, and critical. The algorithm iteratively assigned each data point to the nearest centroid based on the Euclidean distance in the feature space. The resulting clusters were visualized both in three dimensions (SOC, Vbat, Tbat) and in two dimensions (SOC, Tbat), demonstrating a clear separation of the operating states.

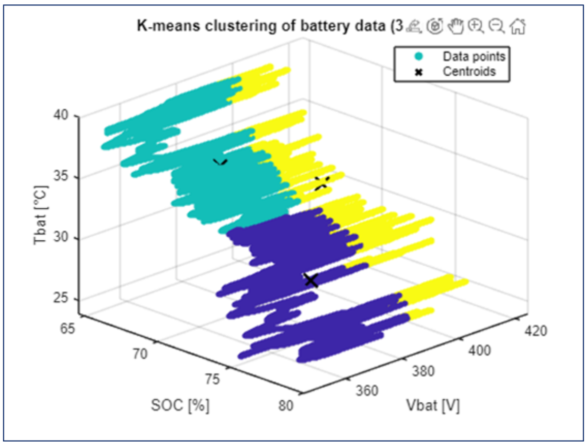

Figure V.6: K-means clustering of battery Data (3D)

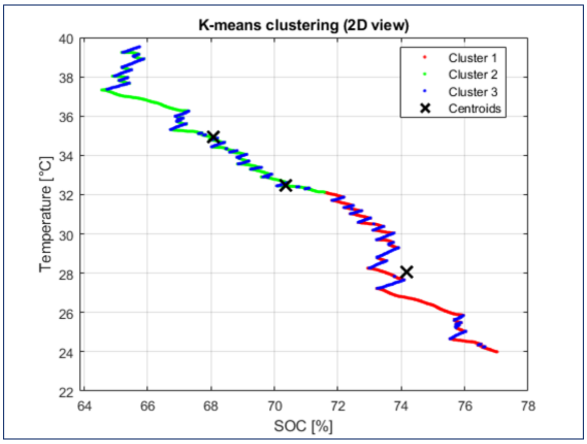

Figure V.7: K-means clustering of battery Data (2D)

While K-means provides an unsupervised partitioning, it does not inherently associate physical meaning with the clusters. To address this, decision rules based on battery operating thresholds were applied to map each cluster to a specific state :

- **Normal :** SOC > 60%, temperature < 40 °C, and low to moderate current demand.
- **Elevated:** Intermediate state with SOC between 30% and 60%, or temperature in the range of 40-50 °C.
- **Critical :** Severe operating condition with SOC < 30%, or temperature exceeding 50 °C, indicating potential safety risks or excessive stress. These rules allow the clusters to be interpreted in terms of realistic battery operating scenarios.

To obtain a predictive model capable of classifying unseen data, a Random Forest algorithm was trained using the features and the cluster-based labels. Random Forest, composed of 100 decision trees in this work, is well-suited for handling nonlinear relationships and heterogeneous data. The Out-of-Bag (OOB) sampling method was employed to validate the model internally, eliminating the need for an external test dataset and providing a reliable estimate of generalization performance.

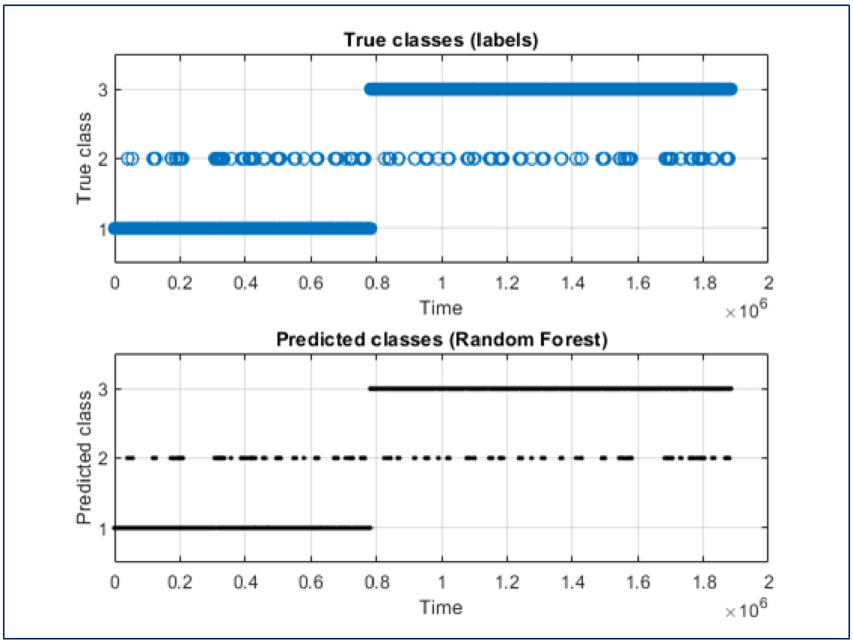

Figure V.8: True classes & predicted classes

The classification outcomes were compared with the reference labels derived from the clustering and logical mapping step. The temporal plots demonstrated strong agreement between the actual labels and the predictions, confirming the Random Forest's ability to reproduce the clustering structure while generalizing to new samples. The 3D visualization further illustrated the accurate separation of classes across the SOCVoltageTemperature feature space.

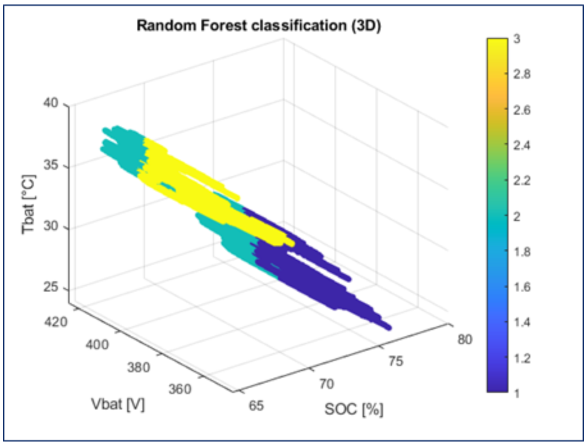

Figure V.9: Random Forest classification

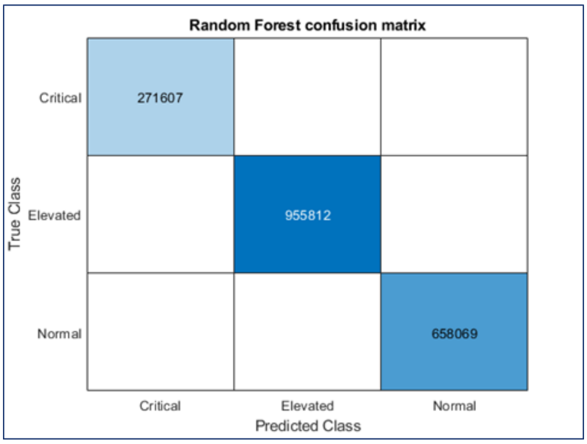

Figure V.10: R.f Confusion Matrix

The performance of the classification model was quantitatively assessed using a confusion matrix. This matrix highlights the proportion of correctly and incorrectly classified samples for each class. The results revealed high accuracy in distinguishing between Normal and Critical states, with occasional misclassifications between Normal and Elevated states, which is expected due to the overlapping physical conditions. The confusion matrix thus provides a precise evaluation of the model's reliability.

Random Forest inherently provides a measure of predictor importance by evaluating the impact of each feature on classification performance. The analysis indicated that SOC and temperature were the most influential predictors, as they directly reflect the energy content and thermal safety of the battery. Voltage and current also contributed meaningfully, but played a relatively secondary role compared to SOC and temperature. This result highlights the importance of monitoring SOC and temperature for effective battery management.

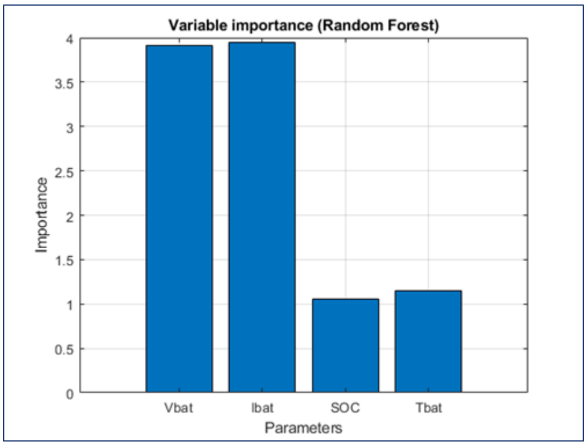

Figure V.11: R.f Variable importance

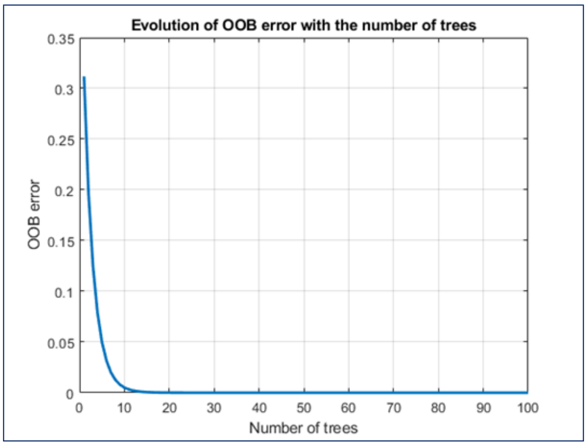

Figure V.12: Evolution OBB error

The Out-of-Bag error was monitored as a function of the number of decision trees. The error curve decreased rapidly at the early stages and stabilized after approximately 80 trees, confirming that 100 trees provide a suitable trade-off between accuracy and computational complexity. This analysis demonstrates the robustness of the Random Forest model and its ability to converge to a stable classification performance.

The proposed methodology combines unsupervised clustering (K-means) with supervised learning (Random Forest) to effectively classify battery operating states during different driving cycles. K-means enables an initial, data-driven segmentation, while logical rules provide physical interpretability to the clusters. Random Forest then consolidates this structure into a predictive model, achieving high classification accuracy and robustness. This hybrid approach offers a reliable tool for identifying and monitoring battery conditions under real-world driving scenarios.

V.5.2 US06 Drive Cycle

US06 depicts aggressive, high-speed driving conditions Figure V.13. It lasts approximately 765 seconds, covers about 13 km, with an average speed of 77.7 km/h and a top speed of 130 km/h. It simulates driving with quick accelerations and decelerations, representing highway merging and passing. Typical speed-time profile: high speeds with rapid changes, ranging from 0 to 130 km/h.

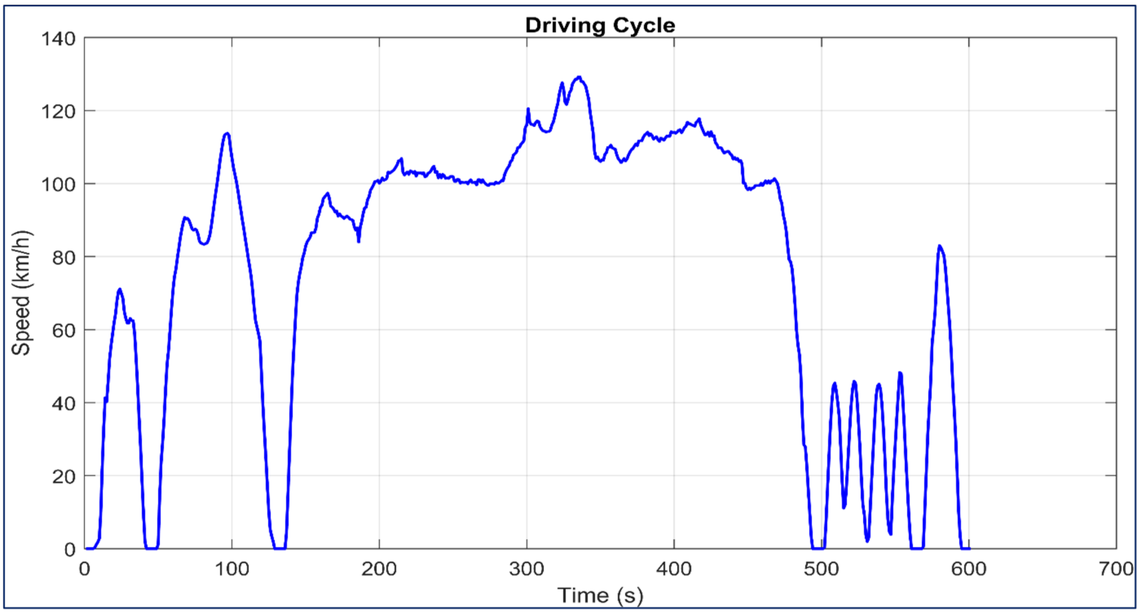

Figure V.13: US06 Drive Cycle

The experimental data were extracted from the standardized driving cycle, US06; the same steps were taken as for the FTP75 drive cycle. The following results were obtained in the same way.

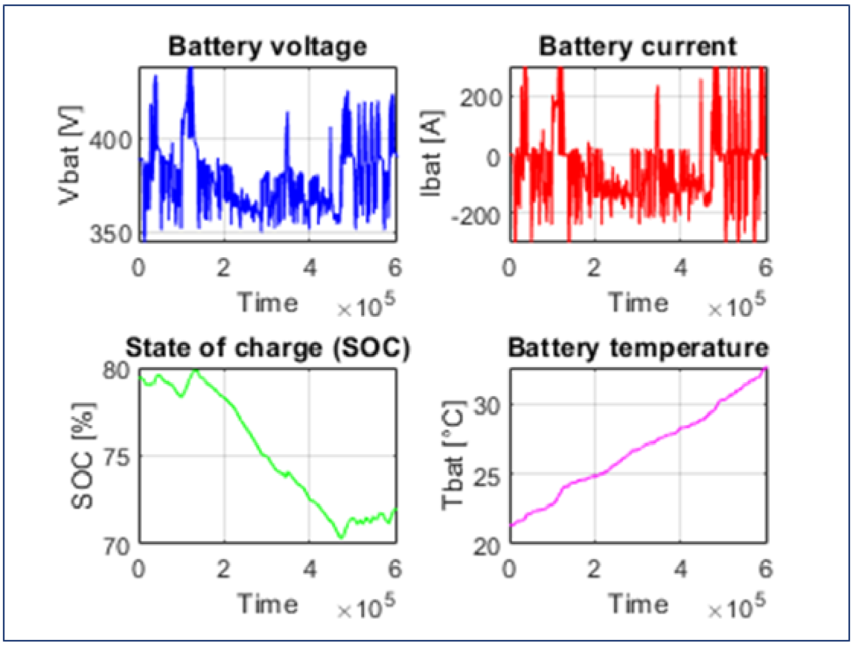

Figure V.14: Signals' raw visualizations.

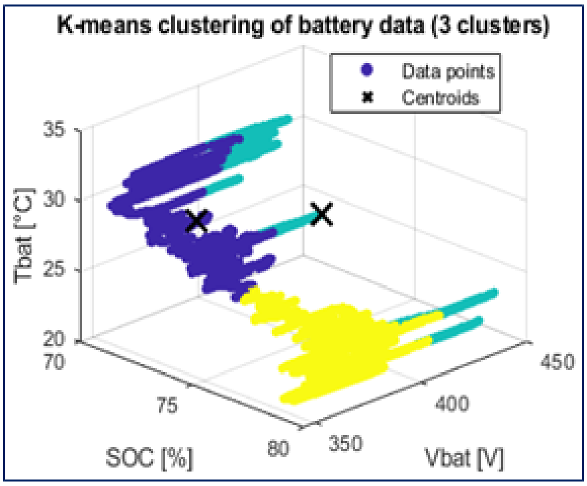

Figure V.15: K-means clustering of battery Data (3D)

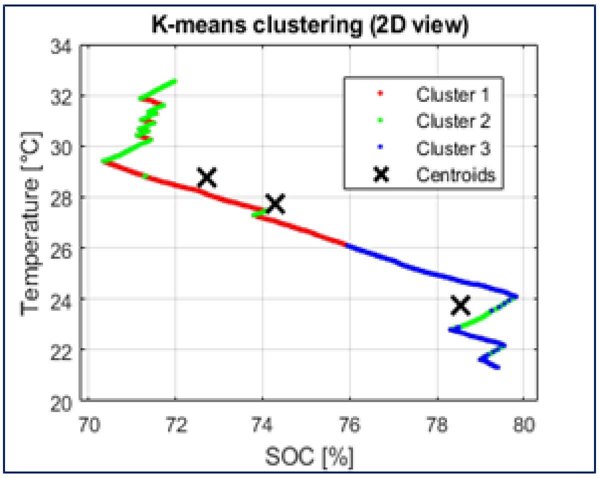

Figure V.16: K-means clustering of battery Data (2D)

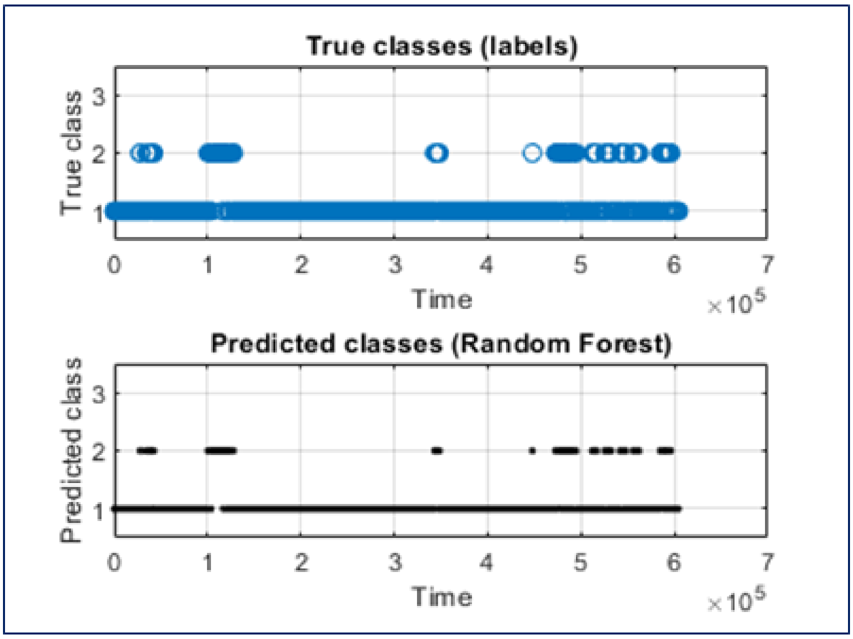

Figure V.17: True classes & predicted classes

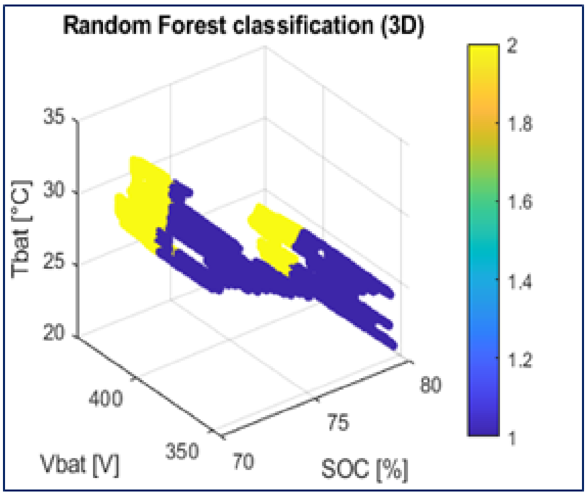

Figure V.18: R.f classification.

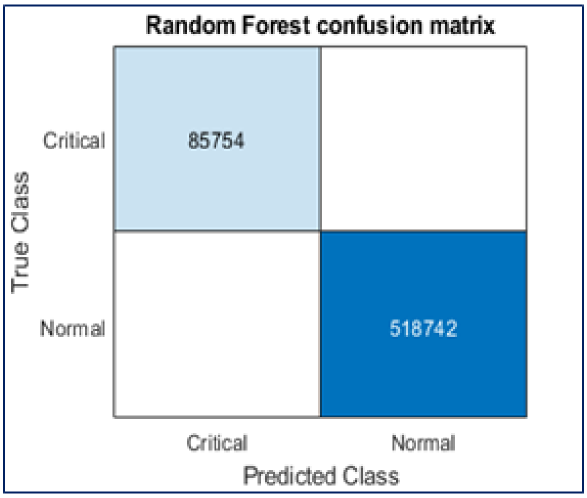

Figure V.19: R.f Confusion Matrix

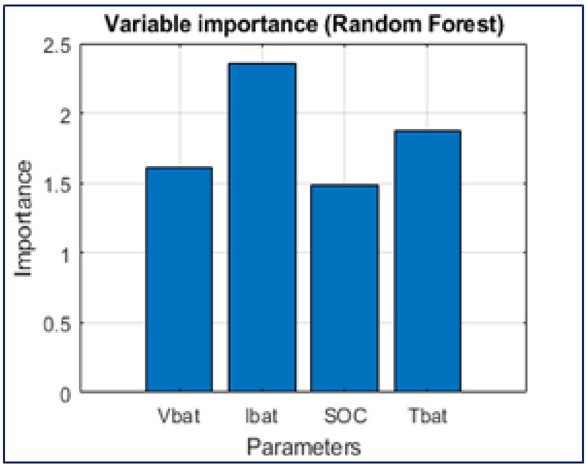

Figure V.20: R.f Variable importance.

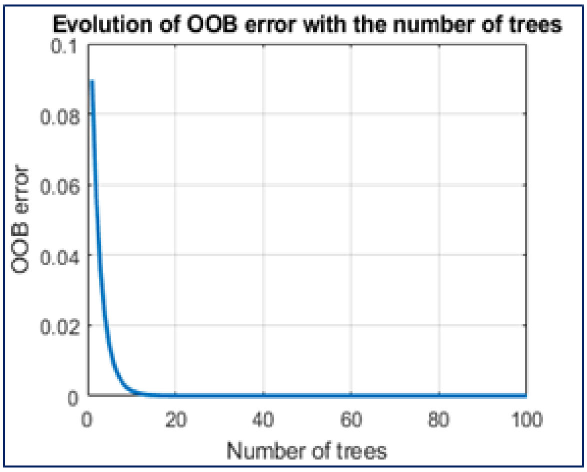

Figure V.21: Evolution OBB error

V.5.3 SC03 Drive Cycle

The SC03 cycle tests vehicle emissions with air conditioning use under hot ambient temperatures (around 35 °C) Figure V.22. It lasts about 596 seconds and covers 5.8 km, with an average speed of 34.8 km/h and a maximum speed of around 88.2 km/h. The driving pattern is urban with several stops and accelerations under AC load. Typical speed-time profile: urban speed variations range from 0 to approximately 88 km/h, with frequent stops and starts.

Figure V.22: SC03 Drive Cycle

The experimental data were extracted from the standardized driving cycle, SC03; the same steps were taken as for the FTP75 drive cycle. The following results were obtained in the same way.

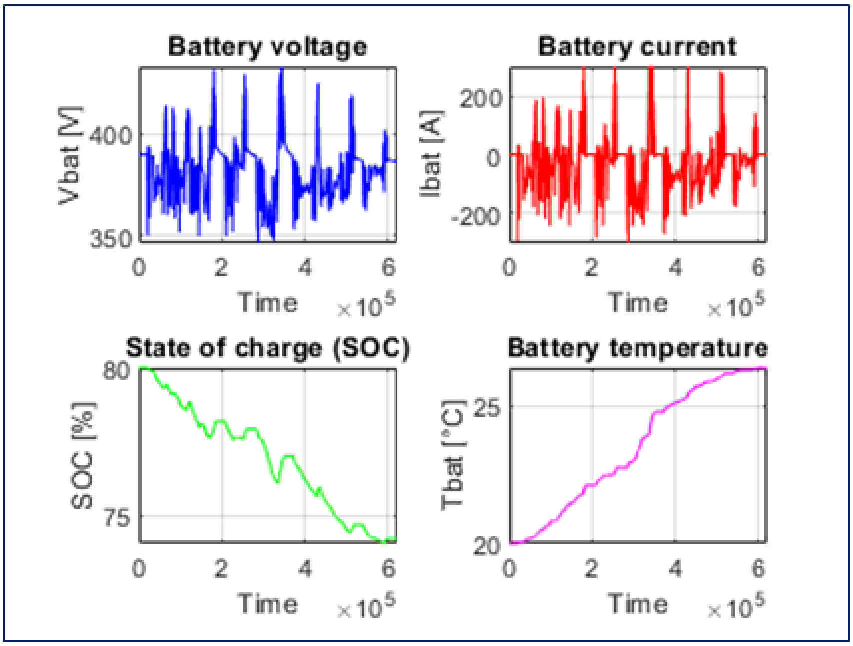

Figure V.23: signals' raw visualizations.

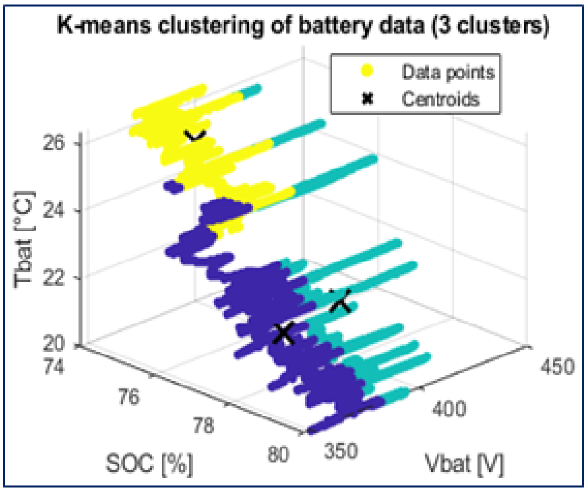

Figure V.24: K-means clustering of battery Data (3D)

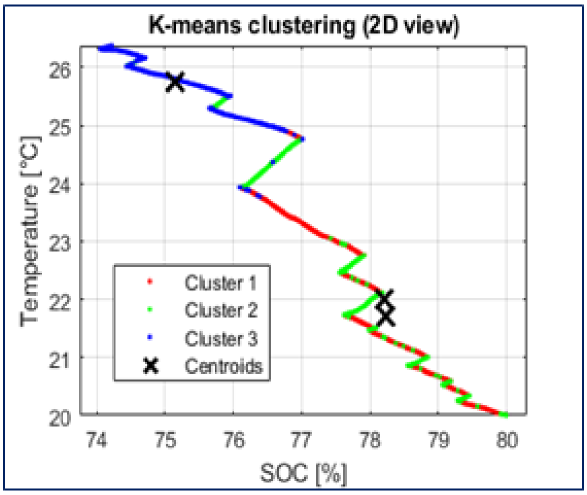

Figure V.25: K-means clustering of battery Data (2D)

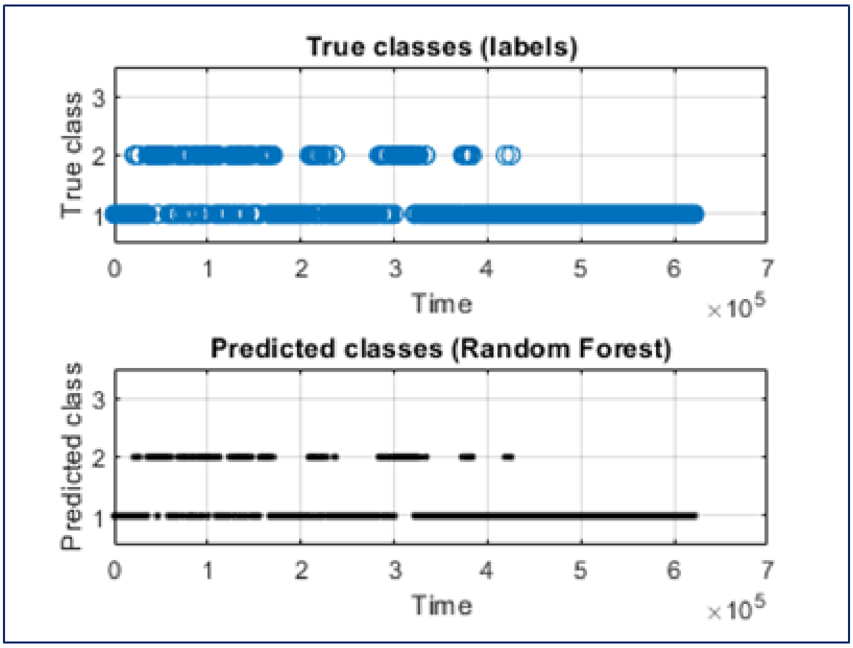

Figure V.26: True classes & predicted classes

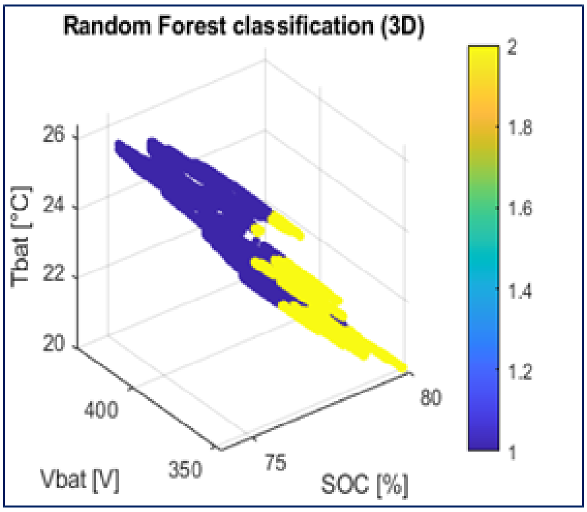

Figure V.27: R.F classification.

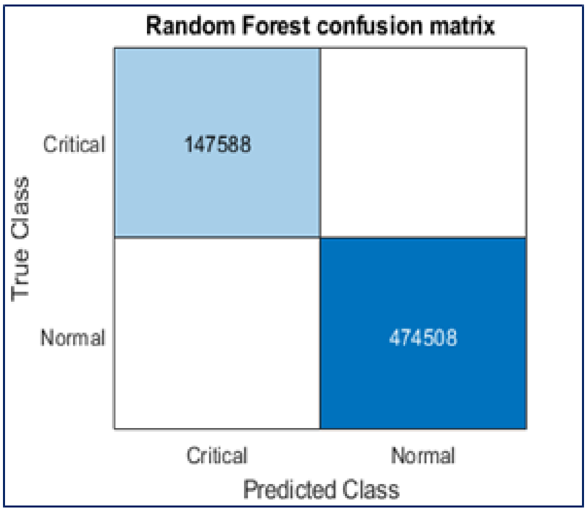

Figure V.28: R.F Confusion Matrix

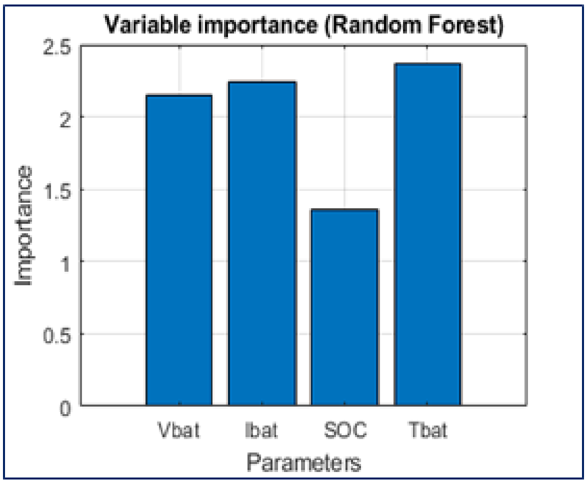

Figure V.29: R.f Variable importance.

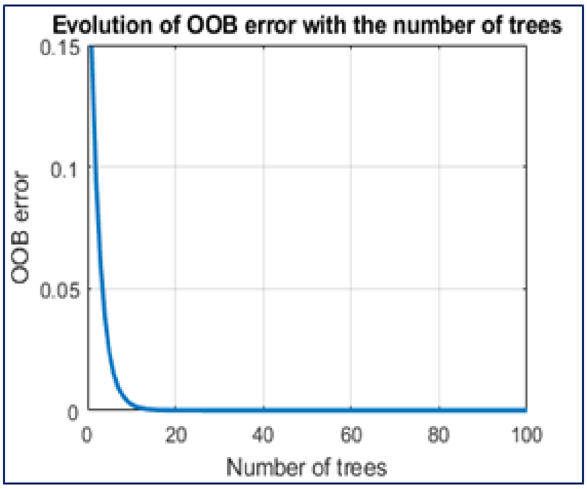

Figure V.30: Evolution OBB error

V.5.4 Highway Drive Cycle

The Highway cycle simulates consistent highway driving at higher, steady speeds (Figure V.31). It lasts about 765 seconds (12-13 minutes), covering roughly 16 km at an average speed of nearly 77 km/h, with a top speed around 97 km/h. Vehicle speed remains fairly steady with fewer stops. Typical speed-time profile: smooth and consistent speeds, mostly between 60 and 100 km/h.

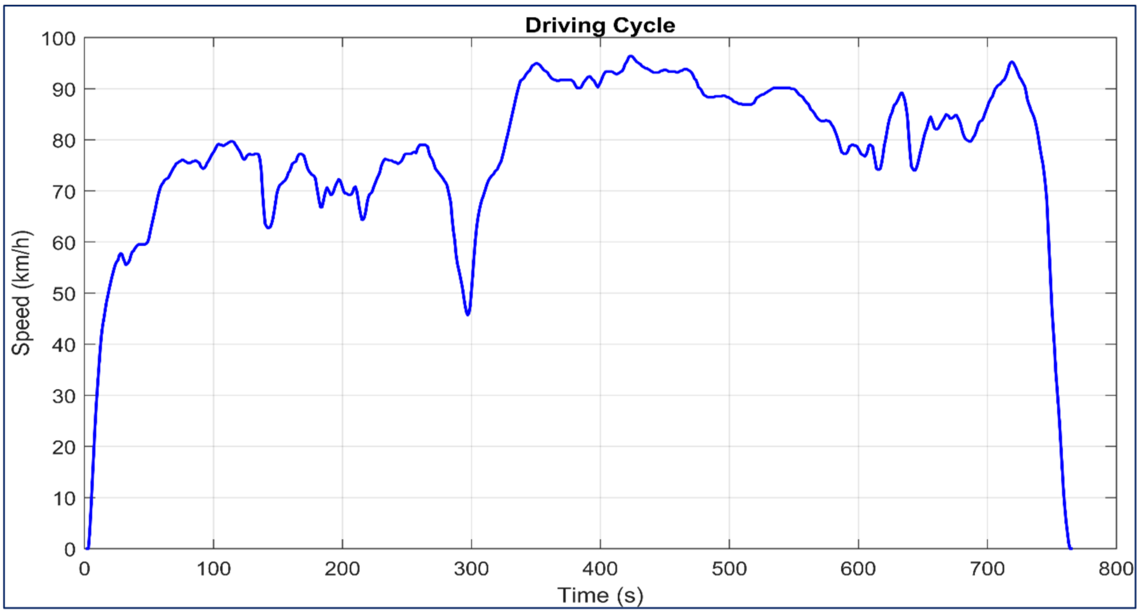

Figure V.31: Highway Drive Cycle

The experimental data were extracted from the standardized driving cycle, Highway; the same steps were taken as for the FTP75 drive cycle. The following results were obtained in the same way.

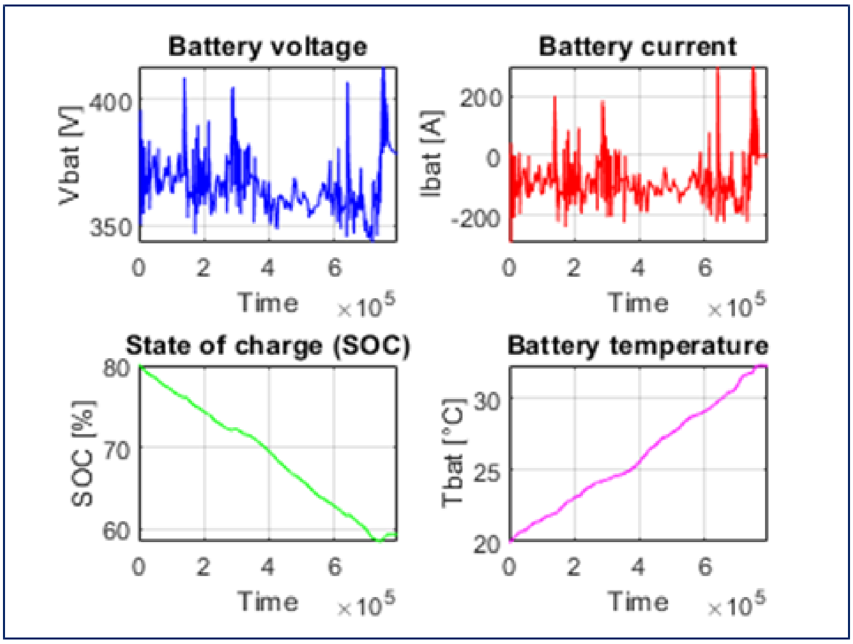

Figure V.32: Signals' raw visualizations.

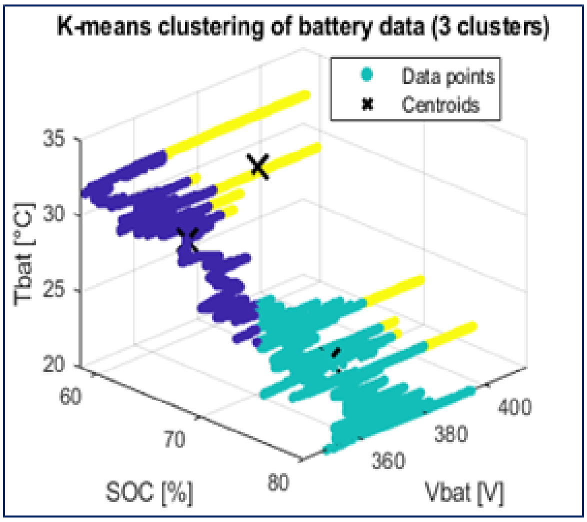

Figure V.33: K-means clustering of battery Data (3D)

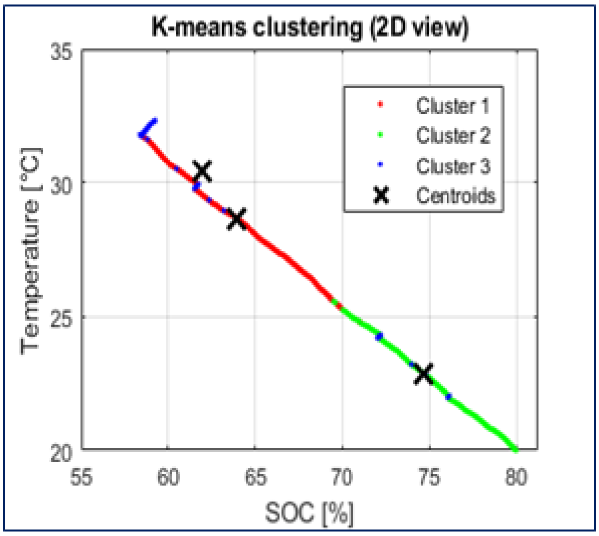

Figure V.34: K-means clustering of battery Data (2D)

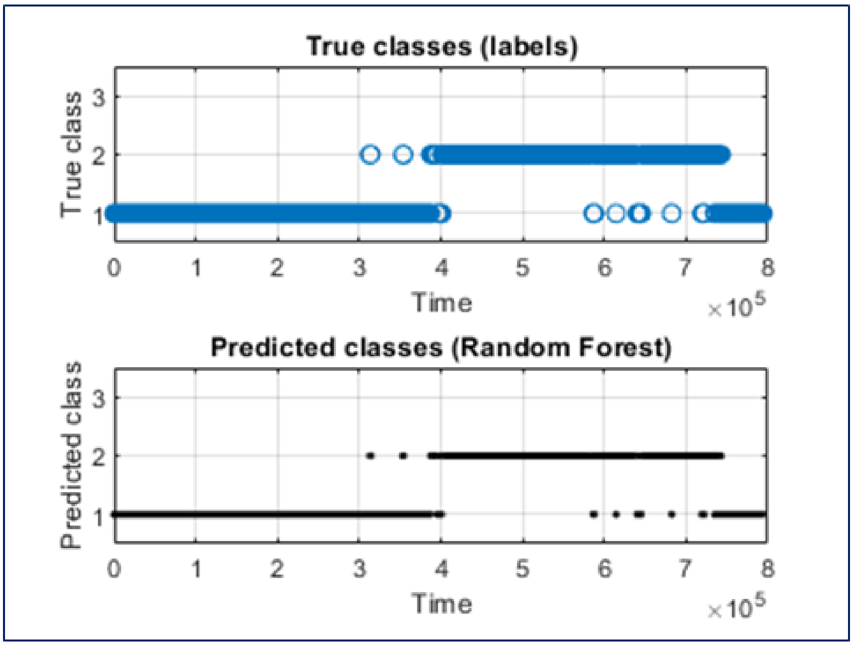

Figure V.35: True classes & predicted classes

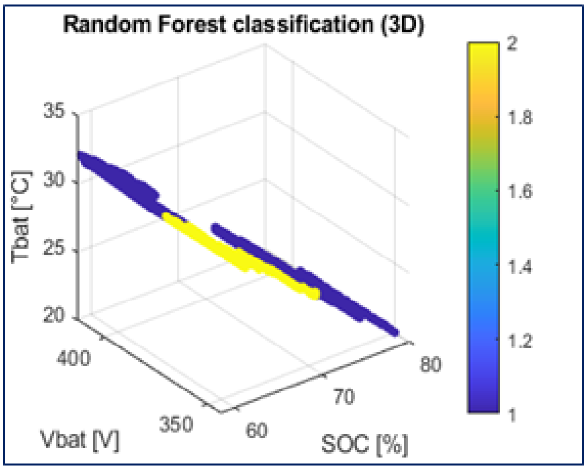

Figure V.36: R.f classification.

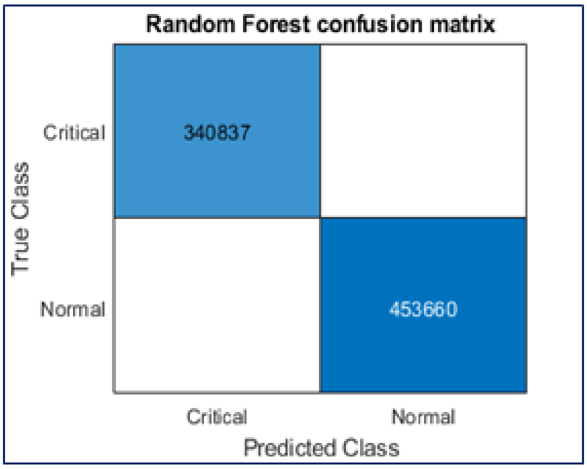

Figure V.37: R.f Matrix

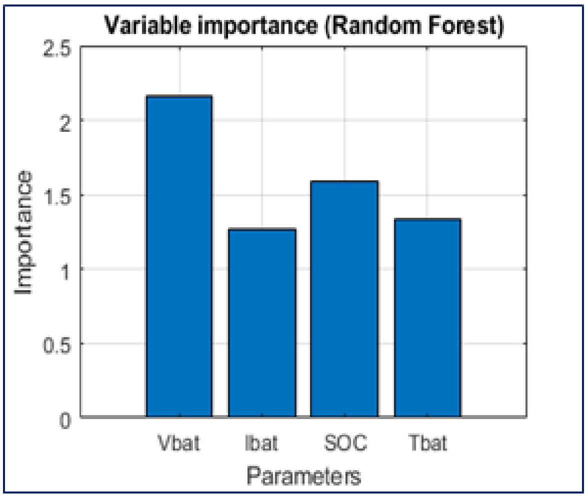

Figure V.38: R.f Variable importance.

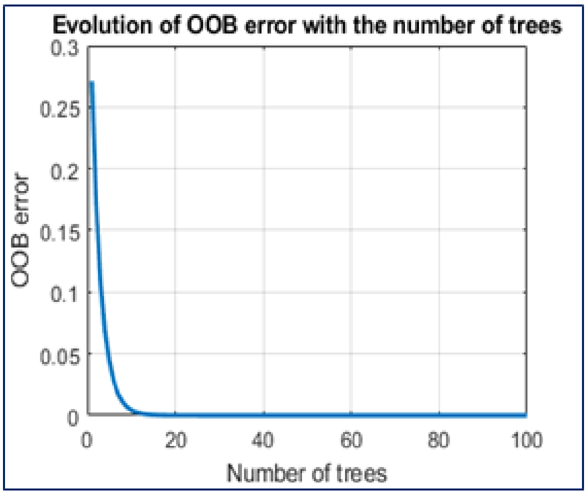

Figure V.39: Evolution OBB error

The comparative evaluation of battery monitoring across the four driving cyclesFTP-75, US06, SC03, and Highwayprovides essential insights into the robustness, generalization, and limitations of the proposed hybrid methodology (K-means + Random Forest). The results highlight both the cycle-specific behaviors of the battery and the consistency of the classification framework.

Dataset size and variability

The number of samples collected differed significantly across the driving cycles, reflecting their duration and load dynamics. The FTP-75 and US06 cycles generated large datasets with highly transient current and voltage variations, resulting from frequent accelerations and decelerations. In contrast, the SC03 cycle produced intermediate-sized datasets that captured the combined effects of air-conditioning load and urban stop-and-go traffic. The Highway cycle generated long-duration but more stable datasets due to continuous cruising conditions. This variability provided a comprehensive validation environment for testing the scalability of the methodology.

Classification performance

The confusion matrices revealed a strong overall accuracy across all cycles, with consistent success in distinguishing between Normal and Critical states. Misclassifications primarily occurred between Normal and Elevated states, which is expected given their overlapping SOC and temperature boundaries.

- **FTP-75:** Achieved the most balanced classification across all three states (Normal, Elevated, Critical), reflecting the diverse and dynamic conditions of this urban cycle.
- **US06:** High-speed and aggressive acceleration patterns increased the occurrence of Critical states. Despite these rapid transients, the Random Forest maintained high predictive accuracy with minimal error.
- **SC03:** This cycle exhibited a larger proportion of Elevated states due to combined thermal effects and auxiliary load. The classifier performed well but showed a slight increase in confusion between Normal and Elevated states.
- **Highway:** With relatively steady conditions, the classifier achieved very high accuracy, with most data classified as Normal and a limited occurrence of Critical states.

Out-of-Bag (OOB) error analysis

Across all cycles, the OOB error decreased rapidly within the first 50 trees and stabilized after approximately 80 trees were reached. This convergence pattern was consistent, confirming the robustness of the Random Forest and justifying the choice of 100 trees. The Highway cycle showed the lowest OOB error due to its steady operating conditions, while US06 presented slightly higher error levels, reflecting the complexity of highly transient load dynamics.

Feature importance

Analysis of predictor importance consistently highlighted SOC and temperature as the most influential variables across all cycles, confirming their universal role in determining battery safety and state of health.

- In FTP-75 and SC03, temperature played a stronger role due to frequent load changes and the impact of auxiliary systems.
- In US06, SOC dominated as aggressive driving rapidly depleted energy reserves, pushing the battery closer to Critical states.
- In Highway, both SOC and voltage were important, reflecting steady discharge conditions and stable current profiles.

Overall, current (Ibat) and voltage (Vbat) acted as complementary variables, enriching model performance but playing a secondary role compared to SOC and temperature.

Temporal prediction stability

The time-series plots confirmed that predicted classes closely followed the accurate labels across all cycles. In dynamic cycles (FTP-75 and US06), the classifier demonstrated strong adaptability to frequent state transitions, while in stable cycles (Highway), predictions remained highly consistent over long durations. The SC03 cycle further confirmed the classifier's capacity to capture intermediate Elevated states, which often occur during mixed driving and auxiliary load conditions.

Comparative Insights

From a broader perspective, the following insights can be drawn:

- **Cycle complexity matters:** More dynamic cycles (US06, FTP-75) increase classification challenges but still yield strong predictive performance, confirming the robustness of the model.
- **Elevated state sensitivity:** The Elevated class is the most challenging to separate, as its boundaries overlap physically with both Normal and Critical states.
- **Universal indicators:** SOC and temperature consistently dominate predictor importance, reinforcing their role as primary parameters for battery monitoring.
- **Robust generalization:** Despite differences in dataset size, variability, and stressors, the methodology generalized effectively across all cycles, confirming its applicability to real-world driving scenarios.

Table V.1: Comparative Summary of Driving Cycles

Criteria	**FTP-75**	**US06**	**SC03**	**Highway**
Dataset Size / Characteristics	Large dataset, high variability due to urban stop-and-go	Large dataset, aggressive accelerations, high-speed	Intermediate dataset; includes A/C load and stop-go	Long dataset, stable cruising conditions
Classification Accuracy	High, balanced across Normal & Elevated & Critical	Very high for Normal & Critical	High, slightly lower for Elevated	Very high, mostly among Normal states
OOB Error Trend	Stabilized after ∼80 trees	Slightly higher than other cycles	Stable after ∼80 trees	Lowest among all cycles
Dominant Predictors	SOC & Temperature	SOC dominant; Temperature secondary	Temperature & SOC	SOC & Voltage
Typical Misclassification	Normal, Elevated	Elevated, Critical	Normal, Elevated	Rare misclassifications
Key Observations	Good robustness to frequent transitions; balanced prediction across classes	Captures Critical states well; some confusion in transients	Sensitive to thermal effects; Elevated class more frequent	Extremely stable predictions; very low Critical state occurrence

V.6 Conclusion

In this chapter, a systematic analysis of battery data classification was performed under four representative driving cycles: FTP-75, US06, SC03, and Highway. By applying the Random Forest algorithm, the classification performance was evaluated in terms of parameter importance, prediction accuracy, out-of-bag (OOB) error behavior, and confusion matrix results.

The findings demonstrate that the prediction capability of Random Forest remains consistently high across all driving profiles, though some variations are observed depending on the cycle dynamics. In urban stop-and-go conditions (FTP-75) and during aggressive high-speed driving (US06), the algorithm effectively captured transient states but exhibited slightly higher misclassification rates between elevated and normal conditions. The SC03 cycle, which incorporates thermal loads, revealed a more substantial influence of temperature, confirming the significance of thermal effects on classification outcomes. In contrast, the Highway cycle yielded the most stable results, characterized by very low OOB error and minimal misclassifications, mainly due to the predominance of steady-state operation.

Overall, the results confirm the robustness of Random Forest for battery state classification under diverse operating conditions. The model adapts well to both transient-rich and steady-state cycles, with the State of Charge (SOC) and temperature emerging as the most critical predictors across scenarios. This comparative evaluation highlights the importance of considering diverse drive cycles for model validation, ensuring that classification systems remain reliable and generalizable to real-world vehicle operation.

General Conclusion and Perspectives

The work presented in this thesis has explored energy management and monitoring in electric vehicles, with a particular focus on integrating advanced optimization algorithms and intelligent monitoring architectures. Over the course of this work, several simulation campaigns and experimental validations were conducted, showing improvements of up to 8-12% in overall energy efficiency compared to baseline rule-based approaches. The research was structured around two principal axes: the design and evaluation of energy management strategies for hybrid and fully electric configurations, and the development of intelligent monitoring frameworks leveraging IoT connectivity and artificial intelligence techniques.

In the first part of this study, various energy management approaches were implemented and analyzed to improve the overall efficiency of electric and hybrid vehicles. Rule-based strategies were initially employed to establish a baseline, followed by advanced methods, including fuzzy logic control and optimization-based techniques. These approaches were tested across multiple standard driving cycles to capture a wide range of operational scenarios, from urban stop-and-go conditions to highway cruising. The comparative analysis highlighted the trade-offs between real-time applicability, computational demand, and achieved energy savings. In particular, fuzzy-logic-based controllers demonstrated robust adaptability to varying driving conditions, while optimization techniques provided a pathway towards minimizing fuel consumption and extending battery lifetime when sufficient computational resources were available.

The second central axis of this work was dedicated to real-time monitoring of the vehicle's energy systems. A comprehensive monitoring-based framework was developed to acquire, process, and classify large-scale data from batteries and cars. The methodology incorporated advanced clustering and classification algorithms to detect anomalies, predict performance degradation, and ensure safe operation under dynamic conditions. The integration of machine learning methods enabled not only the detection of critical states but also predictive capabilities, providing early warnings for potential failures and enhancing overall reliability. Furthermore, the modularity of the proposed monitoring system enables seamless integration with cloud-based platforms, allowing for remote supervision and data-driven optimization.

Overall, the results obtained throughout this research demonstrate that the synergy between intelligent energy management and real-time monitoring offers a powerful avenue towards more efficient, reliable, and sustainable electric mobility. Energy optimization strategies directly contribute to reducing consumption and extending battery lifespan, while intelligent monitoring ensures safety, fault detection, and predictive maintenance. The combination of these two pillars creates a holistic framework that addresses both the efficiency and reliability challenges of electric vehicles.

However, this work also presents several limitations that must be acknowledged. The models and control strategies were primarily validated through simulations under standard driving cycles, which may not fully capture real-world variability. Moreover, hardware implementation and real-time testing were limited to preliminary stages due to constraints in embedded platform resources and communication latency. These limitations open opportunities for deeper experimental validation and the integration of real driving data to refine and validate the proposed approaches.

This thesis thus contributes to the advancement of next-generation electric vehicle technologies by bridging control-oriented energy management methods with data-driven monitoring solutions. The proposed approaches can be further extended by incorporating emerging paradigms such as digital twins, edge computing, and vehicle-to-grid integration, paving the way for future intelligent mobility ecosystems.

Building on these limitations and achievements, future work will focus on the simultaneous integration of energy management and monitoring within a unified real-time framework. The objective is to implement both functions directly in the vehicle, leveraging IoT technologies and artificial intelligence to enable adaptive, predictive, and fully automated decision-making. Such an approach will not only optimize energy consumption under varying driving conditions but also ensure continuous supervision of the battery and powertrain health, thereby enhancing safety and reliability.

From a practical standpoint, future research should emphasize real-time deployment on embedded systems, with secure IoT communication protocols and collaborative cloud-edge architectures capable of processing large data streams in milliseconds. By achieving this dual capabilitymanaging energy flows and monitoring system performance simultaneouslyelectric vehicles will move closer to intelligent, self-managed systems, able to adapt dynamically to both user demands and environmental constraints. This direction represents a decisive step towards the practical application of innovative, autonomous, and sustainable mobility solutions.

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