

République Algérienne Démocratique et Populaire
Ministère de l'Enseignement Supérieur et de la Recherche Scientifique
Université Mohamed Khider de Biskra, Algérie
Faculté des Sciences et de la Technologie
Département de Génie Électrique

Réf :



THÈSE

En vue de l'obtention du diplôme de
Doctorat LMD en Génie Électrique

**Contribution à l'amélioration des performances d'un véhicule
électrique par les méthodes d'optimisation**

Présentée par **M. Mohamed Fadi KETHIRI**

Soutenue le : **12/02/2026**

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People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research
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THESIS

In Candidacy for the Degree of
LMD Doctorate in Electrical Engineering

Contribution to the Improvement of Electric Vehicle Performance Via Optimization Methods

Presented by **Mr. Mohamed Fadi KETHIRI**

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Acknowledgments

"In the name of Allah, the Most Gracious and the Most Merciful"

Allah Almighty said : [31:12] **"Be grateful to Allah, for whoever is grateful, it is only for their own good".**

First and foremost, I would like to express my deepest praise and gratitude to Allah, the Almighty, the Most Gracious and the Most Merciful, for granting me the strength, patience, and health to complete this thesis. Without His guidance and blessings, none of this work would have been possible.

I would like to express my sincere gratitude to my supervisor, Professor **Omar Charrouf**, for his constant guidance, valuable scientific advice, and continuous encouragement throughout this research. His confidence in my abilities and his availability at every critical stage of this work have been a great source of motivation and support.

My heartfelt thanks are also extended to our team leader, Professor **Achour Betka**, for his visionary leadership, scientific insight, and for providing an inspiring research environment within our group. His constructive remarks and encouragement greatly contributed to the progress and quality of this thesis.

I would also like to thank all the professors, researchers, and technical engineers who have supported me at different stages of this work, whether through discussions, laboratory assistance, or technical support.

Great thanks and appreciation are given to the members of the jury: Professor **Naimi Djemai**, President of the jury, Professor **Messaoud Mohammedi**, and Professor **Boualaga Rabhi**, for accepting to evaluate this work, for the time they devoted to reading the manuscript, and for their insightful comments, suggestions, and constructive remarks which helped improve the quality of this thesis.

Above all, my deepest and most special gratitude is dedicated to my beloved parents, for their unconditional love, endless prayers, and unwavering moral and financial support. They have always been my greatest source of strength and sacrifice. I also warmly dedicate this work to my brothers, who have never ceased to encourage me, stand by my side, and share both the difficult moments and the achievements of this journey.

Mohamed Fadi Kethiri

الملخص

إن النمو السريع للمركبات الكهربائية يطرح تحديات ملحة تتعلق بالكفاءة والموثوقية وإدارة الطاقة. وغالباً ما تعجز استراتيجيات التحكم التقليدية عن استغلال الإمكانيات الكاملة لسلاسل الدفع الحديثة، خصوصاً في ظروف التشغيل المتغيرة وغير المؤكدة. تقترح هذه الأطروحة استراتيجيات متقدمة للتحكم والمثلى موجهة نحو محركات التيار المستمر عديمة الفراشي (BLDC) وأنظمة التخزين الهجينة للطاقة في تطبيقات المركبات الكهربائية. يقدم هذا العمل إطاراً مبتكراً يدمج بين نظرية التحكم الكسري، والمنطق الضبابي، وخوارزميات التحسين الميتا-إرشادية مثل خوارزمية أسراب الجسيمات (PSO)، من أجل تصميم متحكمات هجينة ذاتية الضبط قادرة على التكيف في الزمن الحقيقي مع لايقينيات النظام. تم تطوير متحكم PI كسري هجين يعتمد على المنطق الضبابي وخوارزمية PSO (A-HFOPI)، وتمت عملية التحقق منه ليس فقط عن طريق المحاكاة والاختبارات باستخدام تقنية المحاكاة في الحلقة (HIL)، بل أيضاً على منصة تجريبية حقيقية مُصممة كنظام دفع لمركبة كهربائية. بالإضافة إلى ذلك، تم تنفيذ إستراتيجية للتحكم التكيفي في التدفق باستخدام المنطق الضبابي وطريقة الناقلية التزايدية للتحكم الديناميكي في التدفق الإستاتوري، مما ساعد على تقليل الخسائر النحاسية، وخفض القدرة المستهلكة عند المدخل، وتحسين الكفاءة الطاقوية الكلية لمحرك BLDC. تُظهر النتائج أن الاستراتيجيات المقترحة تقلل بشكل ملحوظ من الخسائر الطاقوية، وتحسن دقة التحكم في العزم، وتزيد من فعالية توزيع الطاقة بين وحدات التخزين، وتطيل عمر البطارية، مع الحفاظ على المتانة والاستقرار في مختلف ظروف التشغيل. وتكمن أصالة هذا العمل في الدمج الصريح بين التنظيم التكيفي للتدفق واستراتيجيات التحكم الذكية المعتمدة على الخوارزميات الميتا-إرشادية، وهو نهج مبتكر لم يُطبّق من قبل في هذا السياق. تُسهم هذه الأطروحة في دفع حدود المعرفة في مجال التحكم بالمركبات الكهربائية، حيث تقدم إطاراً عملياً لسلاسل الدفع الحديثة، وتشكّل قاعدة صلبة للبحوث المستقبلية حول أنظمة تحكم تكيفية، آنية، وواعية بالطاقة.

الكلمات المفتاحية: المركبات الكهربائية، محرك BLDC، التحكم الكسري، الخوارزميات الميتا-إرشادية، المنطق الضبابي، إدارة الطاقة.

Abstract

The rapid growth of electric vehicles (EVs) has created pressing challenges in efficiency, reliability, and energy management. Conventional control strategies often fall short in fully exploiting the potential of modern electric powertrains, especially under variable and uncertain operating conditions. This thesis proposes advanced control and optimization strategies for brushless DC (BLDC) motors and hybrid energy storage systems in EV applications. The research introduces a novel framework that integrates fractional-order control theory, fuzzy logic, and metaheuristic optimization algorithms such as Particle Swarm Optimization (PSO) to design hybrid self-tuning controllers capable of real-time adaptation to system uncertainties. A hybrid fuzzy-PSO-based fractional-order PI controller (A-HFOPI) was developed and validated not only through simulations and Hardware-in-the-Loop (HIL) testing but also on a real experimental test bench designed as an electric vehicle traction system. Furthermore, an adaptive flux control strategy based on fuzzy logic and the Incremental Conductance (IncCond) method was implemented to dynamically regulate the stator flux, thereby reducing copper losses, lowering input power consumption, and improving overall energy efficiency during BLDC motor operation. The results demonstrate that the proposed strategies significantly reduce power losses, enhance torque control precision, improve energy allocation between storage devices, and extend battery life, while ensuring robustness and stability across operating conditions. The originality of this work lies in the explicit integration of adaptive flux regulation with intelligent, optimization-based control, a novel approach not previously applied in this context. This thesis thus advances the state of the art in electric vehicle control, offering both a practical framework for modern EV powertrains and a solid foundation for future research on adaptive, real-time, and energy-aware control architectures.

Keywords: Electric Vehicles, BLDC Motor, Fractional-Order Control, Metaheuristic Algorithms, Fuzzy Logic, Energy Management.

Résumé

La croissance rapide des véhicules électriques (VE) soulève des défis pressants en matière d'efficacité, de fiabilité et de gestion de l'énergie. Les stratégies de commande classiques ne parviennent souvent pas à exploiter pleinement le potentiel des chaînes de traction modernes, en particulier dans des conditions de fonctionnement variables et incertaines. Cette thèse propose des stratégies avancées de commande et d'optimisation pour les moteurs à courant continu sans balais (BLDC) et les systèmes hybrides de stockage d'énergie dans les applications de VE. Le travail de recherche introduit un cadre novateur intégrant la théorie du contrôle d'ordre fractionnaire, la logique floue et les algorithmes d'optimisation méta-heuristiques tels que l'optimisation par essaims particulaires (PSO), afin de concevoir des régulateurs hybrides auto-ajustables capables de s'adapter en temps réel aux incertitudes du système. Un régulateur hybride PI fractionnaire basé sur la logique floue et le PSO (A-HFOPI) a été développé et validé non seulement par des simulations et des essais en boucle Hardware-in-the-Loop (HIL), mais également sur un banc d'essai expérimental conçu comme un système de traction pour véhicule électrique. En outre, une stratégie de contrôle adaptatif du flux, fondée sur la logique floue et la méthode de la conductance incrémentale (IncCond), a été mise en œuvre afin de réguler dynamiquement le flux statorique, permettant ainsi de réduire les pertes cuivre, de diminuer la puissance d'entrée et d'améliorer l'efficacité énergétique globale du moteur BLDC. Les résultats démontrent que les stratégies proposées réduisent de manière significative les pertes énergétiques, améliorent la précision du contrôle du couple, optimisent la répartition de l'énergie entre les dispositifs de stockage et prolongent la durée de vie de la batterie, tout en garantissant robustesse et stabilité dans différentes conditions de fonctionnement. L'originalité de ce travail réside dans l'intégration explicite de la régulation adaptative du flux avec des stratégies de commande intelligentes basées sur l'optimisation, une approche novatrice qui n'avait pas encore été appliquée dans ce contexte. Cette thèse contribue ainsi à l'avancement de l'état de l'art dans le domaine du contrôle des véhicules électriques, en offrant à la fois un cadre pratique pour les chaînes de traction modernes et une base solide pour les recherches futures sur des architectures de commande adaptatives, en temps réel et économes en énergie.

Mots-clés : Véhicules électriques, Moteur BLDC, Commande d'ordre fractionnaire, Algorithmes méta-heuristiques, Logique floue, Gestion de l'énergie.

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List of Acronyms

A-HFOPI	Adaptive Hybrid Fractional Order Proportional Integral.
AC	Alternative Current.
ACO	Ant Colony Optimization.
AI	Artificial Intelligence.
BA	Bat Algorithm.
BBA	Binary Bat Algorithm.
BCO	Bee Colony Optimization.
BLAC	Brushless AC motor.
BLDC	Brushless DC motor.
BTMS	Battery Thermal Management System.
COG	Center Of Gravity.
CS	Cuckoo Search.
DC	Direct Current.
DE	Differential Evolution.
DOD	Depth Of Discharge.
DSP	Digital Signal Processors.
DTC	Direct Torque Control.
DWT	Discrete Wavelet Transform.
ECM	equivalent circuit models.
EMI	Electromagnetic Interference.
EMS	Energy Management System.
EV	Electric Vehicle.
FA	Firefly Algorithm.
FC	Fuel Cells.
FL	Fuzzy Logic.
FO	Fractional Order.
FLC	Fuzzy Logic Controller.
FOC	Field Oriented Control.
FOCS	Field Oriented Calculus.
FOPI	Fractional Order Proportional Integral.
FOPID	Fractional Order Proportional Integral Derivative.
FPGA	Field Programmable Gate Arrays.

FWT	Fast Wavelet Transform.
GA	Genetic Algorithms.
GD	Gradient Descent.
GSA	Gravitational Search Algorithm.
GSO	Gravitational Swarm Optimizer.
GWO	Grey Wolf Optimization.
HEV	Hybrid Electric Vehicle.
HESS	Hybrid Energy Storage System.
HIL	Hardware In the Loop.
IAE	Integral Absolute Error.
IDWT	Inverse Discrete Wavelet Transform.
IGBT	Insulated Gate Bipolar Transistor.
IM	Induction Motor.
IMC	Internal Model Control.
IncCond	Incremental Conductance.
ITAE	Integral of Time-Weighted Absolute Error.
LSE	Least Squares Estimation.
MFO	Moth Flame Optimization.
MGO	Mountain Gazelle Optimization.
MHA	Metaheuristic Algorithm.
MIPC	Multi-Input Power Converter.
MPPT	Maximum Power Point Tracking.
MPC	Model Predictive Control.
MRAC	Model Reference Adaptive Control.
NFL	No Free Lunch.
NEDC	New European Driving Cycle.
PDO	Prairie Dog Optimization.
PI	Proportional Integral.
PID	Proportional Integral Derivative.
PMSM	Permanent Magnet Synchronous Motors.
PPA	Plant Propagation Algorithm.
PSO	Particle Swarm Optimization.
PV	Photovoltaic.
PWM	Pulse Width Modulation.

QFT	Quantitative Feedback Theory.
RMS	Root Mean Square.
SA	Simulated Annealing.
SC	Supercapacitors.
SGO	Social Group Optimization.
SOC	State Of Charge.
SVM	Space Vector Modulation.
V2G	Vehicle-To-Grid.
V/f	Volts/Hertz.
VFD	Variable Frequency Drive.
WCA	Water Cycle Algorithm.

Chapter 1

General Introduction

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1.1 Overview

The development of electric vehicles (EVs) dates back to the early 19th century, significantly predating the internal combustion engine vehicles that would later dominate transportation [1]. The first crude electric carriage was developed in the 1830s by Scottish inventor Robert Anderson, with practical electric vehicles emerging by the late 1800s. Between 1890 and 1910, electric vehicles played a considerable popularity, particularly in urban settings where their limited range was less problematic [2].

The early 20th century saw the decline of electric vehicles due to several factors, including the mass production of affordable gasoline vehicles, the expanded road infrastructure enabling longer-distance travel, and the discovery of abundant petroleum reserves. By the 1920s, electric vehicles had almost completely disappeared from the mainstream market.

Interest in electric vehicles was revived during the 1970s oil crisis, which highlighted the vulnerability of petroleum-dependent transportation systems. The electric and hybrid vehicle research, development, and demonstration act of 1976 (PL 94-413) marked a significant milestone, requiring comprehensive data development to characterize electric and hybrid vehicle technologies. During this period, NASA conducted extensive track and dynamometer tests on 22 electric, 2 hybrid, and 5 conventional vehicles to establish performance benchmarks.

The modern era of electric vehicles began in the 1990s with advancements in battery technology and growing environmental concerns [3, 4]. The release of the GM EV1 in 1996 represented the first serious attempt by a major manufacturer to produce a mass-market electric vehicles in the modern era. Although ultimately discontinued, it demonstrated the potential of electric propulsion. The introduction of the Toyota Prius hybrid in 1997 further advanced electrification technologies [1].

The true renaissance of electric vehicles began in the late 2000s driven by rapid advances in battery technology, growing environmental awareness, government incentives for clean transportation, and the rising cost of fossil fuels, with Tesla's introduction of the Roadster in 2008, followed by mainstream models from Nissan (Leaf), Chevrolet (Volt), and others [5]. Since then, electric vehicles have rapidly evolved, with improvements in battery technology, motor efficiency, control systems, and overall performance. Today, electric vehicles are quickly gaining a foothold in global markets, driven by their zero tailpipe emissions, improving practicality, and increasing the competitive total cost of ownership [6].

1.2 Problematic

This thesis is dedicated to the optimization of electric vehicle (EV) design and performance, with a particular emphasis on enhancing energy management and motor control strategies. The successful operation of an EV depends on the effective integration of advanced systems capable of managing energy distribution efficiently and ensuring high-performance motor control. Achieving superior functionality therefore requires addressing a number of technical challenges related to these two fundamental aspects.

From the perspective of energy management, the primary challenge lies in ensuring the efficient allocation and distribution of energy among the various subsystems of the vehicle. The energy storage components—typically composed of batteries and supercapacitors—must be managed in real time to guarantee optimal energy flow, particularly during transient operating conditions such as acceleration and regenerative braking. Current energy management systems often face difficulties in seamlessly integrating multiple energy sources while simultaneously mitigating energy losses, handling thermal constraints, and minimizing battery degradation. This lack of robustness, especially under real-world conditions where driving behavior and environmental variations introduce significant uncertainties, represents one of the key issues addressed in this thesis.

The control of the electric motor, which directly influences vehicle performance, introduces an additional layer of complexity. Motor control strategies must not only ensure the efficient conversion of electrical energy into mechanical motion but also deliver high dynamic performance, including smooth acceleration and deceleration. Although conventional approaches have proven effective in limited operating ranges, they often fail to maintain optimal performance across diverse driving conditions. Advanced control techniques such as Field-Oriented Control (FOC) and Direct Torque Control (DTC) provide improved precision and responsiveness; however, they are often associated with increased computational complexity and reduced robustness under parameter variations. This thesis seeks to overcome these challenges by developing advanced and adaptive motor control algorithms capable of maintaining stability and efficiency across varying load and speed conditions while minimizing torque ripple and energy losses.

Ultimately, the broader objective of this research is to contribute to the development of integrated, high-performance systems for both energy management and motor control in electric vehicles. Such systems are expected to enhance overall energy efficiency, improve driving performance, and extend the lifespan of critical components, notably the energy storage units. By investigating advanced control strategies and real-time optimization techniques,

this work aims to address the limitations that currently hinder the large-scale deployment and practical viability of electric vehicles.

From a broader perspective, this research also explores how the optimization of energy management and motor control strategies can advance the overarching goal of sustainable and efficient EV operation. By developing a robust and intelligent control framework that can be seamlessly integrated into next-generation electric vehicles, this thesis aims to support the competitiveness of EVs in the evolving automotive industry. The implementation of these optimized systems is expected to result in enhanced driving comfort, reduced operational costs, and, ultimately, greater adoption of electric mobility across diverse market segments.

1.3 Objectives and Contributions

The overarching goal of this thesis is to enhance the performance, adaptability, and energy efficiency of electric vehicles through the development of advanced motor control and energy management strategies. The research particularly focuses on improving the robustness and intelligence of motor control systems, ensuring optimal operation under diverse and uncertain driving conditions.

The first objective of this thesis is to develop a new adaptability law governing the parameters of the fractional-order proportional–integral (FOPI) controller. This adaptability law dynamically adjusts the controller parameters in real time according to variations in load, speed, and operating conditions. The corresponding contribution lies in the formulation and implementation of this adaptive mechanism, which enhances the responsiveness, stability, and robustness of the motor control system. By enabling the FOPI controller to self-tune under dynamic conditions, the proposed adaptability law ensures superior performance in both steady-state and transient operations.

The second objective focuses on proposing a novel motor control strategy that guarantees smooth and efficient operation of electric motors across a wide range of load and speed conditions. The contribution involves the design of a hybrid fuzzy–PSO FOPI controller, where fuzzy logic is employed to handle system uncertainties and particle swarm optimization (PSO) is used for real-time optimization of control parameters. This hybrid configuration improves torque response, reduces energy losses, and enhances the dynamic behavior of the electric motor, outperforming conventional control methods such as Direct Torque Control (DTC).

The third objective aims to establish a hybrid control system that integrates both energy

management and motor control subsystems to operate in a coordinated and complementary manner. The corresponding contribution lies in the development of an integrated control architecture that dynamically balances energy flow and motor performance, ensuring higher efficiency, extended driving range, and improved sustainability under various driving conditions.

The fourth objective concerns the evaluation of optimization algorithms for parameter tuning within EV control systems. To this end, the thesis compares several metaheuristic algorithms, including PSO, Grey Wolf Optimization (GWO), and Bee Colony Optimization (BCO), in order to assess their effectiveness in improving control performance. The contribution involves a comprehensive comparative analysis, validated through simulation and real-time experimentation, which demonstrates the relative merits of these algorithms in enhancing speed tracking, disturbance rejection, and system stability.

Finally, the fifth objective addresses the minimization of power losses in electric motors through an adaptive flux control strategy. The proposed approach employs Incremental Conductance (IncCond) and Fuzzy Logic methods to dynamically regulate the stator flux in real time. This contribution results in reduced core and copper losses, improved thermal performance, and increased overall energy efficiency, thereby ensuring stable and optimized operation of electric vehicles under real-world conditions.

1.4 Thesis Structure

This thesis is organized into seven chapters that collectively address the modeling, control, and optimization of electric vehicle systems, with particular emphasis on advanced traction control and hybrid energy management.

Chapter 1 introduces the research context, formulates the main problem statement, and outlines the motivations, objectives, and original contributions of the thesis. A brief overview of the manuscript organization is also provided.

Chapter 2 presents an extensive review of the state of the art in electric vehicle performance optimization. The chapter discusses major technological challenges, energy management strategies, and motor control techniques, with special emphasis on BLDC drives and intelligent control approaches.

Chapter 3 develops detailed mathematical models of the hybrid energy storage system, power electronic converters, DC bus, BLDC motor, and vehicle dynamics. These models form the analytical foundation upon which the proposed control strategies are designed and

validated.

Chapter 4 describes the proposed control strategies. It introduces the rule-based energy management system based on frequency separation, along with the advanced traction control architecture. A major contribution of the thesis—the hybrid fuzzy-PSO self-tuning fractional-order PI controller—is developed and justified in this chapter, together with offline and online optimization procedures.

Chapter 5 presents the simulation, Hardware-in-the-Loop (HIL), and real-time experimental validation of the proposed strategies. The results demonstrate the effectiveness of the EMS, the performance improvements achieved by the advanced traction controller, and the robustness of the real-time implementation on the experimental test bench.

Chapter 6 introduces an additional contribution focused on minimizing power losses through adaptive flux control. Two approaches—Incremental Conductance-based and fuzzy logic-based flux regulation—are formulated, integrated into the DTC framework, and validated through detailed simulations and experiments.

Finally, Chapter 7 summarizes the main contributions and findings of the thesis and outlines promising directions for future work related to real-time implementation, advanced EMS expansions, and predictive control methods for next-generation EV platforms.

Chapter 2

State of the Art in Electric Vehicles Performance

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2.1 Introduction

This chapter provides a concise overview of the state of the art in electric vehicle (EV) optimization, emphasizing control strategies, energy management methods, and component-level challenges that affect performance and efficiency. Key focus areas include battery limitations, control system complexity, and the integration of hybrid energy sources such as batteries and supercapacitors.

Various energy management strategies—ranging from frequency separation and wavelet transforms to model predictive and fuzzy control—are reviewed in the context of hybrid storage architectures. Similarly, electric motor technologies (DC, PMSM, IM, and BLDC) and their respective control strategies (FOC, DTC, predictive control, and AI-based methods) are critically compared.

This literature-based review serves as a foundation for the modeling and control strategies developed in the subsequent chapters. In particular, the next chapter introduces detailed system-level models, including electrochemical storage elements, power converters, and the BLDC traction system.

2.2 Challenges in Electric Vehicle Technology

While offering significant advantages over internal combustion engine vehicles, electric vehicles still face a range of challenges that must be systematically addressed to enable wider adoption, enhanced performance, and economic scalability. These challenges span multiple domains, including electrochemical storage, powertrain control, thermal regulation, system integration, supporting infrastructure, and economic viability.

2.2.1 Battery Technology Limitations

Battery technology remains a principal constraint on electric-vehicle performance and cost [7]. To begin with, energy density typically lies in the range 100–265 Wh/kg, far below the specific energy of gasoline (around 12,000 Wh/kg, acknowledging the lower conversion efficiency on the ICE side) [3, 4]; this disparity compels careful system-level optimization to extract range without excessive mass. At the same time, charging speed is bounded by electrochemical reaction kinetics, thermal management limits, and the availability of high-power infrastructure [8], so aggressive fast-charging must be balanced against safety and longevity. In parallel, cycle life degrades over time because of side reactions and electrode wear; elevated

temperatures can accelerate these mechanisms, progressively reducing usable capacity and vehicle range [9]. Moreover, performance and lifetime are highly temperature dependent, with extremes inducing efficiency penalties and increased safety risk [10]. Finally, upstream resource constraints—particularly around lithium, cobalt, and nickel—raise questions about long-term scalability and sustainability of supply chains [11].

2.2.2 Control System Complexity

On the control side, modern EVs must meet multiple objectives under uncertainty, which creates tight trade-offs that evolve in real time. Foremost, energy efficiency, dynamic performance, thermal protection, and component longevity define a multi-objective problem where gains in one dimension may degrade another [12, 13]. Compounding this, controller effectiveness depends on composite models whose parameters drift with temperature, aging, and tolerances, reducing the robustness of fixed-gain designs [14]. As techniques such as model predictive control and learning-assisted supervisors become attractive, their computational and memory demands challenge embedded platforms and may affect cost and power budgets [15]. In addition, strong reliance on real-time sensing introduces vulnerabilities to noise, latency, and faults, thereby motivating resilient observers and fault-tolerant strategies [16].

2.2.3 Thermal Management

Thermal management is central to safety, efficiency, and durability. At the pack level, maintaining cell temperatures within an optimal window across ambient conditions and load transients reduces degradation rates and limits the risk of thermal runaway [9, 10]. At the power-electronics level, higher switching frequencies and compact packaging elevate heat fluxes, so effective spreading and dissipation are required to sustain reliability [17]. For the electric machine, high torque and speed increase copper and core losses; accordingly, liquid cooling or advanced air-cooling strategies are often needed to control temperature rise [13, 18]. Finally, cabin climate control must deliver comfort with minimal energy draw, which motivates heat pumps, waste-heat recovery, and predictive preconditioning to protect traction batteries and range [19].

2.2.4 System Integration

As EV platforms evolve into tightly coupled electromechanical systems, integration quality increasingly determines overall performance. In terms of hardware, batteries, inverters, mo-

tors, and thermal subsystems must be matched so that sizing and coordination deliver both durability and efficiency [17]. From a controls perspective, energy management, thermal regulation, and motor drives need clear hierarchies and interfaces to prevent antagonistic actions and suboptimal outcomes [20,21]. At the vehicle level, component placement influences dynamics, packaging, and serviceability, forcing trade-offs between performance, structural constraints, and manufacturability [22]. Beyond design, the integration of advanced subsystems raises assembly and quality-control demands with implications for cost and yield [23].

2.2.5 Cost and Market Factors

Economic factors continue to shape adoption and industrial strategy. Upfront prices remain higher than for comparable ICE vehicles, largely due to battery costs [24,25]; meanwhile, limited economies of scale for EV-specific components still affect affordability and throughput [15]. Equally important, resilient supply chains for specialized materials and components are needed to withstand commodity and geopolitical shocks [26,27]. Finally, although operating and maintenance costs are generally lower, total-cost-of-ownership advantages are not always salient to consumers without clear communication and standardized metrics [12,28].

To provide a structured overview of the primary technical challenges in electric vehicle development and their implications for optimization strategies, Table 2.1 summarizes these challenges across the above categories.

Table 2.1: Primary technical challenges in EV development and their implications for optimization strategies.

Challenge Category	Specific Challenges	Implications for Optimization Strategies
Battery Technology	Energy density, charging speed, cycle life, temperature sensitivity	EV energy management optimization, thermal control strategies, charge optimization [9, 10]
Control Systems	Multi-objective control, parameter sensitivity, computational requirements	Advanced algorithms, adaptive control, efficient implementation [12, 13]
Thermal Management	Battery temperature, power electronics cooling, motor cooling	Integrated thermal modeling, predictive cooling strategies [10, 17]
System Integration	Component matching, control coordination, packaging	Multi-domain modeling, optimization approaches [29]
Infrastructure	Charging availability, grid impact, standardization	Infrastructure optimization, V2G strategies, interoperability [8, 30]
Economic Factors	Initial cost, manufacturing scale, lifecycle costs	Sizing optimization, manufacturing process optimization [31]

Addressing these challenges requires interdisciplinary approaches and innovative optimization methods that consider the vehicle as an integrated system rather than as separate components [32, 33].

2.3 Different Topologies Used in Electric Vehicles

Designing an effective energy manager begins with understanding how canonical source–converter interconnections behave in EV powertrains. By varying how high-energy sources (batteries and fuel cells) and high-power buffers (supercapacitors) are tied to the DC bus—directly or via power converters—several families of topologies emerge: passive, active, semi-active, cascade-converter, and multi-input power-converter arrangements. These configurations are used to satisfy both steady-state and transient power demands by exploiting source redundancy and allocating average power to batteries/FCs while reserving fast bursts for SCs, in line with automotive requirements on efficiency, packaging, and cost [34].

Figure 2.1 presents the parallel architectures of hybrid electric vehicles, where the first (top) is the FC–Battery–SC configuration, the second (middle) is the FC–SC configuration, and the third (bottom) is the FC–Battery configuration. These configurations are designed to meet the varying dynamic and steady-state power requirements of electric vehicles.

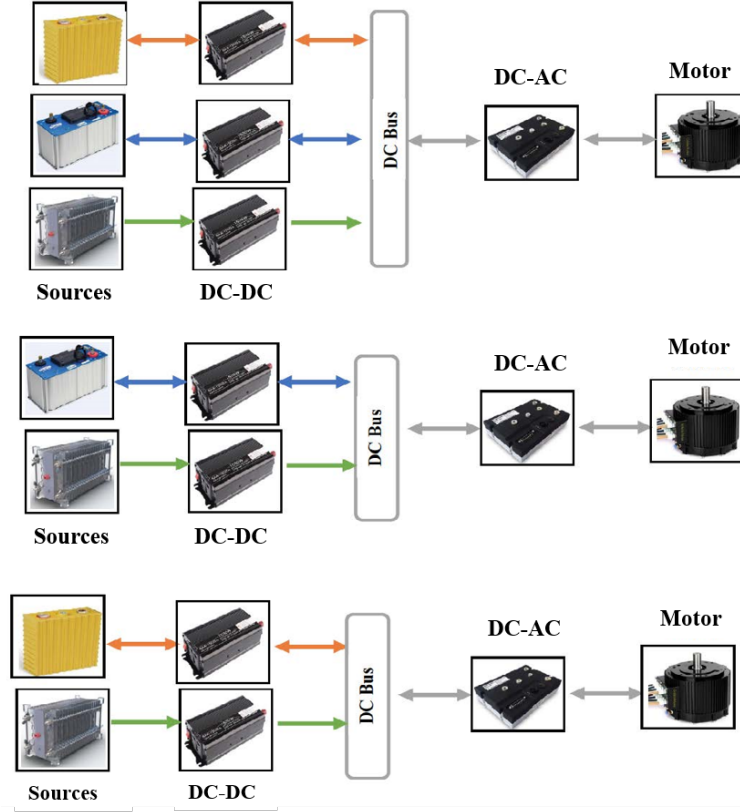


Figure 2.1: Parallel architectures of hybrid electric vehicles; the first (top) is FC–Battery–SC, the second (middle) is FC–SC, and the third (bottom) is FC–Battery.

1. Passive Topology

The passive topology was developed in Ref [35] and is equipped with a battery and SCs as secondary sources, without using DC/DC converters. This topology is cost-effective because of its simple structure and lack of control loops. The main drawbacks are as follows: the energy stored in SCs is not used efficiently, there is no protection against overcurrents, and the system size must be adapted to the bus voltage.

- **Cost-effectiveness:** Inexpensive due to the absence of complex control mechanisms.
- **Limitations:**

- Energy stored in SCs is not efficiently used.
- There was no protection against overcurrents.
- The system size must be adapted to the bus voltage.

Figure 2.2 presents the passive topology, where the energy stored in the supercapacitors is used as a secondary source without complex control mechanisms.

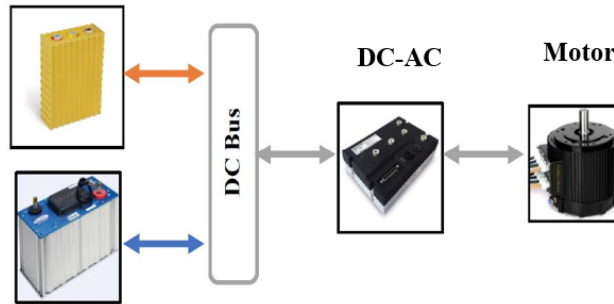


Figure 2.2: Passive topology

2. Active Topology

The active topology is a more advanced approach that uses power converters to actively manage the flow of energy between multiple sources, providing flexibility and better control over the system. It can handle energy more dynamically, optimizing performance across different operating states.

- **Control complexity:** Advanced DC/DC converters are used for better control over energy distribution.
- **Increased flexibility:** Increased adaptability to varying driving conditions.
- **Power management:** This allows efficient power distribution and smoother transitions between different operating states, enhancing performance.

Figure 2.3 shows the active topology, which allows better management of power flow through advanced DC/DC converters.

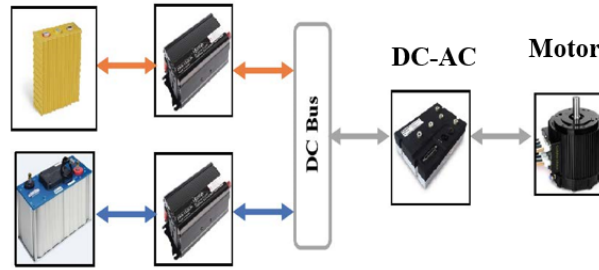


Figure 2.3: Active topology

3. Semi-Active Topology

In Ref [36], the semi-active hybridization topologies involving batteries and supercapacitors (SCs) were studied to enhance power management and system performance. These architectures aim to combine the high energy density of batteries with the high power density of supercapacitors.

Two different semi-active configurations are proposed:

- **Battery/SC semi-active topology:** Figure 2.4 illustrates this configuration, the battery is directly connected to the DC bus, whereas the SC is interfaced via a power converter. This structure simplifies the control by maintaining a relatively constant DC bus voltage and enables an economical system design. However, since the battery currents are not actively regulated and significant current fluctuations can occur, leading to a reduced battery lifespan and a potential decrease in autonomy of up to 50% [36].
- **SC/Battery semi-active topology:** Figure 2.5 depicts this configuration that connects the SC directly to the DC bus, while a converter actively manages the battery's energy flow. This setup allows for fast and efficient energy delivery during the acceleration and deceleration phases, resulting in a threefold improvement in peak power over that of passive hybridization and a fivefold improvement compared to systems based solely on lithium-ion batteries [36].

The key advantages of the SC/Battery topology include the following:

- **Improved performance:** Significant enhancement of system responsiveness during dynamic events.
- **Enhanced energy management:** The converter actively regulates battery currents, reducing stress and extending battery life.

- **Simplified control loops:** Direct connection of the SC to the DC bus eliminates complex voltage regulation for high-speed power demands.

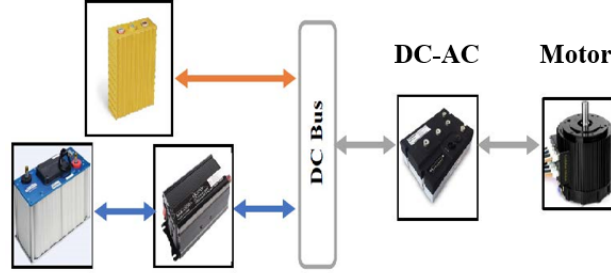


Figure 2.4: Semi-active topology (Battery/SC).

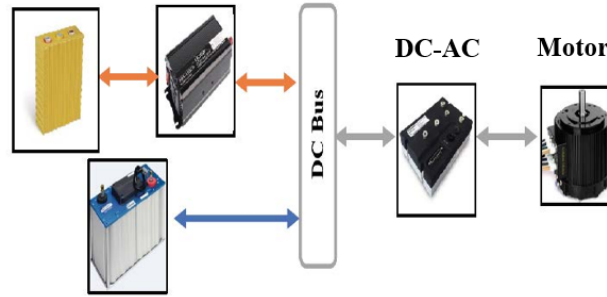


Figure 2.5: Semi-active topology (SC/Battery).

4. Cascade Converter Topology

In [25], a hybrid storage system using a cascade converter was presented. The hybridization of both sources provides a higher power output than each source individually does while maintaining a high energy density.

- **High power output:** The hybridization of both sources provides very high power.
- **Disadvantages:** The use of converters with high nominal power increases the overall system cost.

Figure 2.6 presents the cascade converter topology, which combines both sources for higher power output while maintaining a high energy density.

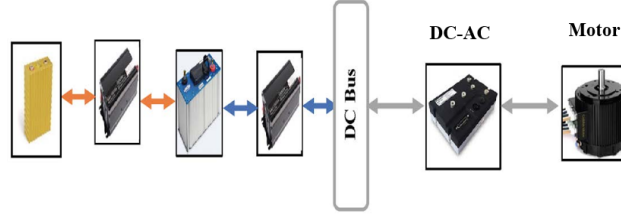


Figure 2.6: Cascade converter topology

5. Multi-Input Power Converter (MIPC)

A multi-input power converter (MIPC) configuration was explored in [37], which involves a power converter responsible for managing the energy flows in each operating mode of the electric vehicle.

- **Flexible energy management:** The MIPC allows for greater flexibility in energy management.
- **Efficient design:** The design is optimized on the basis of various factors such as traction drive and driving cycles.

Figure 2.7 shows the MIPC topology, which allows flexible and efficient energy management for electric vehicles.

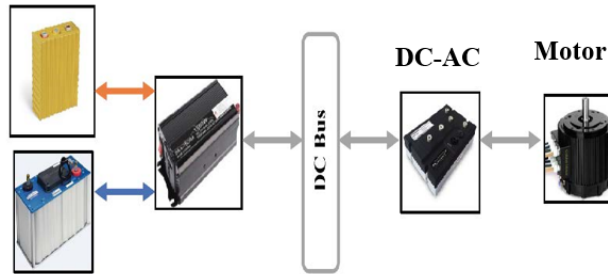


Figure 2.7: Multi-input topology

2.4 Energy Management Control Used in Electric Vehicles

Energy management control strategies in hybrid energy storage systems (HESSs) are designed to distribute the traction power demand among multiple sources (typically battery

and supercapacitor) while respecting their physical limits and maximizing system efficiency. Among the most widely studied families are frequency-based and wavelet-based strategies, which exploit the spectral content of the load current or power to match low-frequency energy to high-energy sources and high-frequency transients to high-power devices.

2.4.1 Frequency-based Energy Management Strategies

Frequency-based energy management strategies partition the load current into slowly varying and rapidly varying components, then assign these components to the battery and supercapacitor, respectively. The separation is usually achieved by a low-pass filter acting on the measured load current $i_L(t)$ or power $P_L(t)$. A first group of works employs a fixed cut-off frequency. In a typical fixed frequency-based EMS, the load current is decomposed into low- and high-frequency parts by a first-order low-pass filter [38, 39]:

$$H_{LP}(s) = \frac{1}{\tau s + 1} \quad (2.1)$$

$$\tau = \frac{1}{2\pi f_c} \quad (2.2)$$

where f_c is the chosen cut-off frequency. The reference current for the battery is obtained from the filtered component, while the reference of the supercapacitor is defined as the complementary part.

$$I_{b,ref}(s) = H_{LP}(s) I_L(s) \quad (2.3)$$

$$I_{sc,ref}(s) = I_L(s) - I_{b,ref}(s) \quad (2.4)$$

This approach is simple and effective in reducing the battery current ripple and improving its lifetime, but its performance is very sensitive to the choice of f_c . If f_c is too low, the supercapacitor is overused; if it is too high, the battery is forced to handle excessive high-frequency content, accelerating aging [38].

To overcome this limitation, adaptive frequency-based strategies adjust the cut-off frequency online according to operating conditions, typically using the supercapacitor state of charge (SOC) as an indicator of available power capability [38]. A common scheme defines three operating regions with associated cut-off frequencies $f_{c,min}$, $f_{c,nom}$ and $f_{c,max}$: when the SC SOC is high, a low cut-off $f_{c,min}$ is selected so that the SC absorbs most of the high-frequency content; when the SOC is low, a higher $f_{c,max}$ shifts more current to the battery; in normal SOC ranges, an intermediate value $f_{c,nom}$ balances the contribution of both sources. This dynamic tuning improves power sharing over different driving cycles and helps maintain

both sources within safe operating conditions [38–40]. Figure 2.8 summarizes a typical adaptive frequency-based EMS: the measured load current is filtered by a tunable low-pass filter whose cut-off frequency is updated from an SOC-dependent logic; the filter output defines $I_{b,\text{ref}}$, while its complement defines $I_{sc,\text{ref}}$, both tracked by DC/DC converters connected to the battery and supercapacitor.

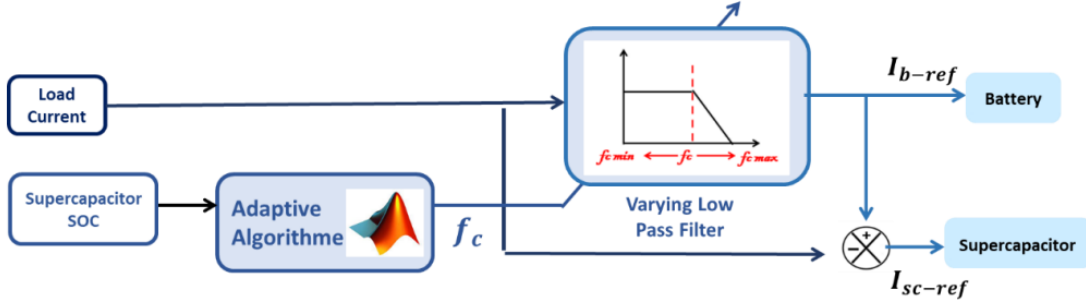


Figure 2.8: Illustrative structure of an adaptive frequency-based EMS. [41]

2.4.2 Wavelet-based Energy Management System

Wavelet-based energy management strategies extend the frequency-based concept by using time–frequency analysis to distinguish between slow and fast components of the load current. Unlike classical filtering, wavelet transforms provide multi-resolution information, enabling a finer separation of transient peaks from the average power demand [39, 40].

In a conventional wavelet-based EMS, the load current (or power) signal $x(t)$ is processed with a discrete wavelet transform (DWT). The continuous form of the wavelet transform is

$$W(\lambda, u) = \int_R x(t) \frac{1}{\sqrt{\lambda}} \psi\left(\frac{t-u}{\lambda}\right) dt \quad (2.5)$$

where $\psi(t)$ is the mother wavelet, λ is a scale factor and u is a time-shift parameter [40]. In practice, compactly supported wavelets such as Haar or Daubechies are used for real-time implementation [42]. After decomposition, the approximation coefficient A_n (low-frequency content) is assigned to the battery,

$$i_{b,\text{ref}} = A_n \quad (2.6)$$

while the sum of detail coefficients $D_1, \dots, D_n$ (high-frequency components) sets the supercapacitor reference,

$$i_{sc,\text{ref}} = D_1 + D_2 + \dots + D_n \quad (2.7)$$

This mapping ensures that rapid power variations and transient peaks are preferentially supplied by the SC, thereby reducing battery stress and improving the overall efficiency of the HESS [40, 42].

More recent works propose adaptive wavelet-based EMSs, where the decomposition level and/or the selection of coefficients are updated online according to the SC SOC, the discharge rate or driving-pattern indicators [42–44]. When the SC has high SOC, higher decomposition levels are activated so that more high-frequency content is routed to the SC; when SOC is low, the decomposition depth is reduced and a larger portion of the load is shifted back to the battery, preserving SC energy. Sliding-window implementations of the DWT are typically adopted to enable real-time processing on embedded controllers, with constraints linking the window length to the chosen decomposition level for accurate reconstruction [43, 44]. Figure 2.9 shows a representative wavelet-based EMS architecture: the load current is processed by a sliding window and DWT block, which produces approximation and detail components; a reconstruction block generates $i_{b,\text{ref}}$ and $i_{sc,\text{ref}}$ according to the selected decomposition level, itself adjusted by an SOC-based supervisory algorithm.

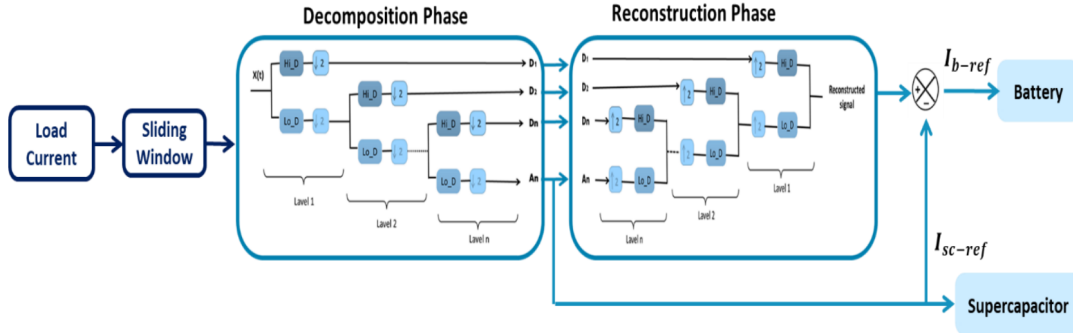


Figure 2.9: Illustrative wavelet-based EMS. [41]

2.4.3 Advanced Predictive and Adaptive Control

Modern energy management systems increasingly employ sophisticated predictive and adaptive techniques:

- **Model Predictive Control (MPC):** MPC optimizes the energy distribution over a prediction horizon, accounting for constraints and multiple objectives.
- **Reinforcement Learning:** Learns optimal energy management policies through interaction with the vehicle and environment.

- **Adaptive Control:** Adjusts control parameters on the basis of changing conditions and system characteristics.
- **Neural Network Control:** Neural networks are used to model complex system behavior and optimize control decisions.

These advanced techniques enable the following:

- Adaptation to driver behavior and preferences.
- Integration of route and traffic information.
- Consideration of battery aging effects.
- Optimization for varying environmental conditions.

Real-time monitoring and optimization form the foundation of effective EV energy management systems. By continuously collecting and analyzing data on energy usage both within the vehicle and on the broader grid, these systems can make dynamic adjustments to ensure efficient energy use, enhance vehicle performance, and reduce strain on electrical infrastructure [11, 33, 45, 46]. Among these advanced techniques, several well-known strategies have already been applied and widely discussed in the literature. Table 2.2 presents a comparative analysis of various energy management strategies, highlighting their advantages and disadvantages.

Table 2.2: Comparative analysis of energy management strategies.

Ref	EM Strategy	Advantages	Disadvantages
[47]	Deterministic rule-based	Simple, reliable and robust, low computation complexity, easy to implement	Not adaptive and poor parametric calibration
[48]	Frequency separation	Simple and easy implementation	Not robust, filter design is difficult
[49]	Fuzzy logic based	Robust and good with model uncertainties and state variations, real time implementable	Dependent on membership functions, optimal control is not guaranteed
[50]	Neural network	More robust to new information, real time implementable	Large amount of training data is needed; stability is not guaranteed
[51]	Dynamic programming	Global optimal solution is found, optimal control, easy to solve nonlinear optimization problems	Not real time implementable, requires heavy computational burden
[52]	Pontryagin's principle	Easy to adapt and simple to implement, no additional controllers required	Computation burden is heavy
[53]	Instantaneous optimization	Optimal value is found at each instant	Not guaranteed to be optimal
[54]	Particle swarm optimization	Minimal computation time, best optimal solution can be found, easy to implement	High-speed controller is required to implement in real time with large memory
[55]	Simulated annealing	Can search for best optimal point after the local optimum	Larger search space is required
[56]	Model predictive control	Potential for real-time implementations; easy to handle constraints directly in the design procedure	May compromise with model accuracy by using linearized model; may need large memory for heavy computations

2.5 Types of Electric Motors Used in Electric Vehicles

Electric motors constitute the core propulsion units of electric vehicles (EVs), converting electrical energy into mechanical torque. The choice of motor technology has a direct influence on vehicle efficiency, dynamic performance, reliability, cost, and overall system complexity. Over the years, several types of electric motors have been investigated and employed in EV applications, including direct current (DC) motors, induction motors (IM), permanent magnet synchronous motors (PMSM), brushless DC motors (BLDC), and switched reluctance motors (SRM). Each of these motor types presents distinct advantages and limitations in terms of efficiency, power density, control complexity, and material cost.

Although a wide range of electric motors has been proposed for EV propulsion, the historical development and large-scale deployment of electric vehicles have been dominated by four major motor technologies: DC motors, induction motors, permanent magnet synchronous motors, and brushless DC motors. These four motor types represent the most significant milestones in EV propulsion history, from early electric vehicles relying on DC machines to modern high-performance EVs employing advanced AC motor technologies.

DC motors were among the earliest solutions adopted in electric vehicles due to their simple control structure and high starting torque. However, their reliance on mechanical commutators and brushes led to increased maintenance requirements and reduced reliability, limiting their suitability for modern EV applications. Induction motors subsequently gained popularity, particularly in high-power EVs, owing to their robust construction, absence of permanent magnets, and good performance over a wide speed range.

Permanent magnet synchronous motors and brushless DC motors represent the most widely adopted solutions in contemporary electric vehicles. These motors offer high efficiency, high power density, and excellent torque characteristics, making them well suited for traction applications. PMSMs are particularly favored in high-end EVs for their superior efficiency and smooth torque production, while BLDC motors are commonly employed in light electric vehicles and auxiliary traction systems due to their simple structure, high torque at low speeds, and ease of implementation.

In summary, while numerous electric motor technologies have been explored for electric vehicle propulsion, DC motors, induction motors, PMSMs, and BLDC motors remain the four most influential and widely utilized motor types in the historical and technological evolution of electric vehicles. Their continued adoption reflects a balanced trade-off between performance, efficiency, reliability, and cost in EV drivetrain design. In the following subsections, each of these four electric motor technologies is presented in detail, including their

operating principles, advantages, limitations, and suitability for electric vehicle applications.

2.5.1 DC Motors

1. Basic Principle

Direct current (DC) motors are among the earliest electrical machines used for propulsion, operating on the basic principle that a conductor carrying current within a magnetic field experiences a force perpendicular to both the current and the field. Their construction typically includes a rotating armature connected to a commutator and brushes, and a stationary field magnet that provides the magnetic flux. The mechanical commutation process continuously reverses current flow in the armature windings to maintain torque generation. DC motors exist in various forms, such as series-wound, shunt-wound, compound, and permanent-magnet configurations, each offering distinct torque–speed characteristics. Speed control is usually achieved by varying the armature voltage, while torque is proportional to armature current. Historically, their simple control and linear torque–speed behavior made them suitable for early electric vehicles [17].

2. Advantages and Limitations of DC Motors

DC motors are historically significant and continue to be used in various applications, but they present both advantages and limitations that influence their practical use, particularly in the context of modern electric vehicles. Table 2.3 provides a summary of the key advantages and limitations associated with DC motors, offering a concise overview of their characteristics and challenges:

This table summarizes the main characteristics of DC motors, including their advantages such as simple control, high starting torque, and cost-effectiveness, as well as their limitations, such as mechanical wear, lower efficiency, and cooling challenges. Despite these drawbacks, DC motors continue to find applications in scenarios where their benefits—especially simplicity and high torque—outweigh their limitations. However, their gradual replacement by more efficient technologies, such as AC motors, is evident in modern electric vehicle designs, where efficiency and longevity are paramount. Nevertheless, DC motors are still relevant in specific auxiliary systems and cost-sensitive applications [57].

Table 2.3: Summary of advantages and limitations of DC Motors.

Advantages	Limitations
Simple control via voltage regulation	Brush and commutator wear requiring regular maintenance
High starting torque, especially in series-wound configurations	Lower efficiency (75-80% vs. 90-95% for AC motors)
Linear torque-speed characteristics	Lower power-to-weight ratio compared to alternative technologies
Low starting current compared to some AC motors	Speed limitations due to commutation constraints
Established technology with extensive development	Electromagnetic interference (EMI) from brush arcing
Cost-effective for basic models	Cooling challenges due to rotor heat generation

2.5.2 Permanent Magnet Synchronous Motors

1. Basic Principle

Permanent magnet synchronous motors (PMSMs) have become a cornerstone of modern electric vehicle propulsion systems due to their superior efficiency and torque performance. They operate through the interaction between the magnetic field produced by permanent magnets on the rotor and the rotating magnetic field generated by three-phase currents in the stator windings. The rotor rotates synchronously with this field, resulting in precise torque and speed control. Modern PMSMs employ rare-earth magnets, such as neodymium-iron-boron, which offer high magnetic flux density and power density. The stator, equipped with distributed or concentrated windings, generates the rotating magnetic field controlled via advanced vector control algorithms—most commonly field-oriented control (FOC)—to ensure optimal torque production. The operating principle of PMSMs is founded on magnetic field alignment, where the rotor flux continuously follows the rotating stator field [13].

2. Advantages and Limitations of PMSMs

PMSMs have become the dominant motor technology in modern electric vehicles because of their exceptional performance characteristics. Table 2.4 summarizes the key advantages and limitations of PMSMs, providing a concise overview of their benefits and trade-offs:

Table 2.4: Summary of advantages and limitations of PMSMs.

Advantages	Limitations
Superior efficiency (92-97%)	Cost premium due to reliance on rare-earth materials
Exceptional power density (30-50% higher power-to-weight)	Supply chain concerns related to rare-earth material production
Excellent torque characteristics from zero speed	Temperature sensitivity (risk of demagnetization at high temperatures)
Smooth operation with minimal torque ripple	Field weakening limitations compared to induction motors
Compact size for equivalent power output	Requires sophisticated electronic control systems
Effective heat management with stator cooling	
No brushes or slip rings to wear out	

These advantages have led to the widespread adoption of PMSMs in electric vehicles from manufacturers including Tesla (newer models), BMW, Nissan, Chevrolet, and virtually all premium EV manufacturers. The superior efficiency of these methods directly translates to an extended range and reduced battery requirements [6]. However, the high performance of PMSMs comes with certain trade-offs, as outlined in the table. Notably, their reliance on expensive rare-earth materials increases manufacturing costs, and their susceptibility to temperature-induced demagnetization and the need for sophisticated control systems present ongoing challenges. Research continues to address these limitations, with efforts focused on reducing the reliance on rare-earth materials, improving thermal management, and advancing control technologies [18].

2.5.3 Induction Motors

1. Basic Principle

Induction motors (IMs), also known as asynchronous motors, operate based on electromagnetic induction, eliminating the need for permanent magnets or electrical connections to the rotor. When a three-phase alternating current flows through the stator windings, it produces a rotating magnetic field that induces currents in the rotor conductors. These induced cur-

rents create a secondary magnetic field that interacts with the stator field to generate torque. The rotor always rotates slightly below the synchronous speed, a condition known as “slip,” which is necessary for torque production. Typical designs employ a squirrel-cage rotor made of conductive bars embedded in a laminated core, and a stator with distributed windings similar to those of PMSMs. Because of their robustness, cost-effectiveness, and absence of rare-earth materials, induction motors remain a reliable and widely adopted option in electric vehicle propulsion [12].

2. Advantages and Limitations of IMs

Induction motors offer compelling advantages that have made them a viable alternative to PMSMs in electric vehicle applications. Table 2.5 summarizes the key advantages and limitations of induction motors, highlighting their role in electric vehicle applications.

Table 2.5: Summary of advantages and limitations of induction motors.

Advantages	Limitations
Robust construction with no permanent magnets or windings	Lower efficiency (85-92% vs. 92-97% for PMSMs)
Excellent durability and resistance to harsh conditions	Lower power density, requiring larger motors for equivalent power
Lower material cost (no rare-earth materials required)	Rotor thermal management challenges due to heat generation
Supply chain security with widely available materials	Requires sophisticated control algorithms for optimal efficiency
Manufacturing scalability with mature production processes	Lower power factor, especially at partial loads
Thermal robustness (no demagnetization concerns)	Efficiency variations across operating range
Extended speed range with good field-weakening capability	

These characteristics have led to the adoption of induction motors in many electric vehicles, most notably in earlier Tesla models (Model S, Model X). Tesla demonstrated that induction motors could deliver competitive performance in premium electric vehicles [28].

Compared with PMSMs, induction motors present several disadvantages, including lower efficiency (typically 85-92% compared with 92-97% for PMSMs), lower power density, and

longer rotor thermal management. Additionally, induction motors require sophisticated control algorithms for optimal efficiency and can suffer from power factor limitations, especially at partial loads. These limitations have led to advancements in induction motor technology, such as copper rotor designs, optimized lamination, and improved control algorithms. These developments have helped maintain the viability of induction motors in electric vehicles, particularly where cost-effectiveness and durability are prioritized over maximum efficiency [18].

2.5.4 Brushless DC Motors

1. Basic Principle

Brushless DC (BLDC) motors combine the structural simplicity of DC machines with the efficiency and control precision of AC drives. They operate using electronic commutation, where semiconductor switches replace mechanical brushes and commutators to achieve phase current switching in synchronization with rotor position. The rotor typically consists of permanent magnets, while the stator has concentrated windings driven by three-phase electronic inverters. Unlike PMSMs, BLDC motors are designed to produce trapezoidal back-electromotive force (EMF) waveforms, making them suitable for six-step commutation control. Rotor position is commonly detected using Hall-effect sensors, encoders, or estimated through sensorless algorithms. This electronically controlled commutation process ensures maintenance-free operation, compact design, and high power density, making BLDC motors an attractive choice for electric vehicles and auxiliary systems [58].

2. Advantages and Limitations of BLDC Motors

BLDC motors offer impressive performance characteristics that make them well-suited for electric vehicle applications. Table 2.6 summarizes the key advantages and limitations of BLDC motors, highlighting their strengths and challenges:

These advantages have led to the widespread adoption of BLDC motors in various electric vehicle applications, particularly in smaller EVs, e-bikes, e-scooters, and as auxiliary motors in larger vehicles. Their superior efficiency and maintenance-free operation have made them a preferred choice in applications where longevity and reduced maintenance are critical [17].

However, BLDC motors face certain limitations compared with other motor types. They require sophisticated electronic controllers and position sensors, which adds to the system complexity and cost [59]. Additionally, the need for more complex implementations and limited field weakening capabilities restricts their performance in some high-speed applications.

Table 2.6: Summary of advantages and limitations of BLDC motors.

Advantages	Limitations
Excellent efficiency (90-95%) across a wide range	Control system requirements (need for electronic controllers and position sensors)
High power density (superior power-to-weight ratio)	Higher initial cost compared to brushed DC motors
Maintenance-free operation (no brushes or commutators)	More complex implementation than simple DC motors
Improved heat dissipation (stator easier to cool)	Limited field weakening (restricted constant-power speed range)
Reduced EMI (no brush arcing)	Torque ripple due to six-step commutation
Extended operational life (longer service life)	
Precise speed control (electronic commutation)	
Low acoustic noise (reduced vibration)	

The torque ripple produced by six-step commutation can also affect performance, especially in precision applications. Modern advancements in BLDC control, including field-oriented control and optimized magnet configurations, have helped mitigate some of these challenges, allowing BLDC motors to compete closely with PMSMs in term of performance [17].

To better understand the trade-offs between different electric motor types used in electric vehicles, Table 2.7 presents a comparative analysis. It highlights key characteristics such as efficiency, power density, control complexity, and notable applications of DC motors, induction motors, PMSMs, and BLDC motors:

Table 2.7: Comparative analysis of the primary electric motor types used in EVs.

Characteristic	DC Motors	Induction Motors	PMSM	BLDC
Efficiency	75-80% [17]	85-92% [28]	92-97% [13]	90-95% [58]
Power Density	Low	Medium	High	High
Control Complexity	Low	Medium-High	High	Medium-High
Cost	Low-Medium	Medium	High	Medium-High
Maintenance	High	Low	Low	Low
Field Weakening	Limited	Excellent	Limited	Limited
Reliability	Medium	High	High	High
Cooling Requirements	High	Medium-High	Medium	Medium
Notable EV Applications	Early EVs, Auxiliaries	Tesla (early models)	Tesla (newer models), BMW, Nissan	Smaller EVs, e-bikes, auxiliary systems

The selection of motor type for a specific electric vehicle application depends on the balance of efficiency, cost, reliability, and performance requirements. Ongoing research continues to enhance all motor types, with a particular focus on improving efficiency, reducing costs, and optimizing control strategies [12, 13].

2.6 Control Strategies for Electric Motors

The control strategy employed for electric motors significantly impacts vehicle performance, efficiency, and drivability. Modern electric vehicles utilize increasingly sophisticated control approaches to optimize motor operation across varying conditions.

2.6.1 Scalar Control

Scalar control, or Volts-per-Hertz (V/f) control, is one of the earliest and simplest methods for AC motor control. It maintains a constant voltage-to-frequency ratio to keep the magnetic flux approximately constant, enabling speed regulation without needing a detailed motor model. This open-loop technique is computationally efficient, sensorless in basic implementations, and easy to deploy in low-cost industrial systems. Its implementation ranges

from basic open-loop versions to enhanced variants with slip compensation, IR compensation, and current limiting [17].

However, scalar control is generally unsuitable for electric vehicle applications. It offers poor dynamic response, limited torque and speed accuracy, and lacks field-weakening capabilities or transient handling. Its inability to directly control torque or respond efficiently at low speeds renders it ineffective as a primary traction control strategy. Even with enhancements, scalar control fails to deliver the performance required for main propulsion systems in EVs [13, 58].

2.6.2 Vector Control (Field-Oriented Control)

Vector control, also known as field-oriented control (FOC), enables high-performance torque and flux control of AC motors by emulating the control characteristics of DC machines. Through Clarke and Park transformations, it decouples stator currents into orthogonal d- and q-axis components, facilitating independent control of flux and torque. This method provides fast dynamic response, high efficiency, smooth torque production, and full four-quadrant operation, making it the most widely adopted control technique in modern electric vehicle drives.

The main drawback of FOC is its computational complexity and dependency on accurate motor parameters and real-time estimations of rotor position. Implementations require advanced digital processors (e.g., DSPs or FPGAs) and incorporate sensor-based or sensorless estimation methods. Despite this, its proven efficiency, dynamic performance, and precision have made FOC the standard among leading EV manufacturers, with ongoing research focusing on adaptive FOC variants to address parameter uncertainties and enhance real-time performance [13, 17, 18].

2.6.3 Direct Torque Control

Direct Torque Control (DTC) offers an alternative to vector control by directly regulating stator flux and torque without requiring current controllers or coordinate transformations. DTC utilizes hysteresis-based torque and flux controllers and selects appropriate inverter voltage vectors via a switching table. It is structurally simpler and offers extremely fast torque response, minimal computational requirements, and reduced dependency on motor parameter accuracy. These features make DTC attractive for EV applications that require rapid torque control under tight resource constraints.

Nevertheless, DTC presents challenges such as variable switching frequency, higher torque ripple (especially at low speed), and sensitivity to stator resistance estimation. It also demands high sampling rates and accurate flux estimators. Modern improvements like Space Vector Modulated DTC (SVM-DTC), predictive control, and duty cycle optimization have mitigated several of these issues. While less prevalent than FOC in commercial EVs, DTC remains valuable in scenarios requiring fast torque regulation and computational simplicity [13, 58].

2.6.4 Modern Control Techniques

1. Adaptive Control

Adaptive control techniques adjust control parameters on the basis of changing operating conditions or motor parameters:

- **Model Reference Adaptive Control (MRAC):** This compares the response of the real system to that of a reference model and adjusts the parameters to minimize discrepancies.
- **Self-Tuning Control:** Continuously estimate the system parameters and adjust the controller settings accordingly.
- **Gain Scheduling:** Selects precalibrated controller parameters based on operating conditions.
- **Parameter Estimation:** Online identification methods are used to track changing motor parameters.

Adaptive approaches are particularly valuable in electric vehicles because of the following:

- Parameter variations with temperature (resistance, magnetic properties).
- Changes in battery voltage throughout the discharge cycle.
- Component aging effects.
- Manufacturing tolerances.

Research has demonstrated that adaptive control can maintain optimal performance despite up to 50% variation in motor parameters, significantly improving efficiency under varying conditions [60].

2. Predictive Control

Predictive control strategies use system models to forecast future behavior and optimize control actions:

- **Model Predictive Control (MPC):** Optimizes control actions over a prediction horizon, considering constraints and multiple objectives.
- **Finite Control Set MPC (FCS-MPC):** This method directly considers the discrete nature of inverter switching states.
- **Deadbeat Control:** This calculates the control action to reach the reference in the minimum time.
- **Explicit MPC:** Precomputes control laws to reduce online computational requirements.

These approaches offer several advantages:

- Explicit handling of system constraints (current limits, voltage limits).
- Multiobjective optimization capability.
- Incorporation of future reference trajectories.
- Systematic treatment of delays and nonlinearities.

Compared with conventional FOC, the implementation of predictive control in electric vehicles has demonstrated efficiency improvements of 3-7%, particularly in transient operations [61].

3. Artificial Intelligence in Control

Artificial intelligence techniques are increasingly applied to electric motor control:

- **Fuzzy Logic Control:** This uses linguistic rules to handle uncertainties and nonlinearities.
- **Neural Network Control:** Learns complex system behaviors through training.
- **Reinforcement Learning:** Developing optimal control policies through interaction with the system.

- **Genetic Algorithms and Metharistics:** Optimizes controller parameters through evolutionary principles.

AI-based approaches offer unique capabilities:

- Handling complex, nonlinear behaviors is difficult to perform analytically.
- Adaptation to changing conditions without explicit modeling.
- Learning from operational data to improve performance over time.
- Dealing with multiple, sometimes conflicting objectives.

Recent research has demonstrated that AI-augmented control systems can improve efficiency by 5-10% compared with conventional approaches, particularly in various driving conditions [33]. Variable frequency drive (VFD) technology, which adjusts motor speed and torque by varying frequency and voltage, represents one of the most widely implemented control techniques across applications ranging from small HVAC systems to large industrial motors. Modern VFDs incorporate increasingly sophisticated control algorithms, often combining elements of FOC, DTC, and adaptive techniques to optimize performance [33]. To provide a clear overview of various motor control strategies in electric vehicles, Table 2.8 compares the key characteristics of different control techniques, including scalar control, FOC, DTC, and predictive control.

Table 2.8: Comparison of motor control strategies for electric vehicle applications.

Characteristic	Scalar Control	Vector Control (FOC)	Direct Torque Control	Predictive Control
Control Principle	V/f ratio	d-q current components	Torque and flux hysteresis	Model-based optimization
Dynamic Response	Poor	Excellent	Very Good to Excellent	Excellent
Torque Accuracy	Poor	Very Good	Good	Very Good
Computational Complexity	Low	High	Medium	Very High
Parameter Sensitivity	Medium	High	Low	Medium-High
Low-Speed Performance	Poor	Excellent	Good	Excellent
Torque Ripple	High	Low	Medium-High	Low
Implementation Complexity	Low	High	Medium	Very High
Sensorless Capability	Limited	Good	Very Good	Good
EV Applications	Auxiliary motors	Primary traction (most EVs)	Selected EVs	Research, premium Electric Vehicles

The selection of control strategy depends on specific application requirements, available computational resources, and performance targets. Modern electric vehicles increasingly implement hybrid approaches that combine elements from multiple control strategies to optimize performance across different operating conditions [19].

2.6.5 Overview of Motor Control Strategies in Electric Vehicles

To provide a quantitative overview of recent research activity on electric motor control strategies for EV traction applications, a numerical bibliographic analysis was conducted covering the period from 2020 to 2025. The analysis was based on structured keyword searches

performed using Google Scholar, restricted to peer-reviewed journal articles published in major Scopus-indexed venues, including IEEE, Elsevier, Springer, IET, and MDPI journals. Only studies explicitly addressing EV traction systems were retained, while review-only, non-traction, and conference-only publications were excluded. Table 2.9 summarizes the resulting distribution of publications according to motor type and control strategy.

Table 2.9: Distribution of journal publications on EV motor control by motor type and control strategy (2020–2025).

Motor Type	Control Strategy	Number of Publications
BLDC	Scalar	11
	Field-Oriented Control (FOC)	54
	Direct Torque Control (DTC)	14
	Optimization / Intelligent	47
PMSM	Scalar	9
	Field-Oriented Control (FOC)	112
	Direct Torque Control (DTC)	41
	Optimization / Intelligent	68
Induction Motor (IM)	Scalar	17
	Field-Oriented Control (FOC)	36
	Direct Torque Control (DTC)	22
	Optimization / Intelligent	19
DC Motor	Scalar	4
	Field-Oriented Control (FOC)	9
	Direct Torque Control (DTC)	3
	Optimization / Intelligent	6
Total Publications		472

From a motor-type perspective, PMSM-based traction systems dominate the literature, accounting for approximately **48.7%** of the publications. BLDC motors follow with **26.7%**, reflecting their growing relevance in low- and medium-power EV applications. Induction motors represent **19.9%** of the studies, while conventional DC motors account for less than **5%**, indicating their progressive obsolescence in modern EV traction systems.

In terms of control strategies, FOC remains the most widely adopted approach, representing approximately **44.7%** of the publications. This confirms its status as the industrial reference for high-performance electric drives. Optimization-based and intelligent control methods, including metaheuristic optimization, fuzzy logic, fractional-order control, and predictive techniques, account for nearly **29.7%** of the literature, highlighting a strong and sus-

tained research trend toward adaptive and high-efficiency traction control. DTC represents approximately **17.0%** of the publications, while scalar control methods are now marginal, with less than **9%** of the total.

Based on these quantitative observations, it is evident that advanced control strategies applied to BLDC and PMSM drives constitute an active and relevant research area. In particular, the combination of DTC with intelligent and optimization-based techniques emerge as a promising solution for improving dynamic performance and efficiency. Accordingly, this thesis adopts a DTC-based traction control framework applied to a BLDC motor, enhanced by advanced control methods, in order to contribute to this growing body of research and address the specific challenges of electric vehicle propulsion systems.

2.7 Conclusion

This chapter reviewed the key technological challenges, energy storage topologies, and control strategies relevant to the optimization of electric vehicle performance. It highlighted limitations in battery technology, control complexity, and system integration, while presenting various energy management strategies and electric motor types used in current EV platforms.

Among the surveyed methods, hybrid energy storage systems combining batteries with supercapacitors have shown notable improvements in power delivery and efficiency. Similarly, motor control has evolved from basic scalar control to advanced vector, direct torque, and optimization-based approaches.

These insights provide the necessary context for the system modeling efforts presented in the following chapter. Chapter 3 develops mathematical and control-oriented models of the key EV subsystems—including lithium-ion batteries, supercapacitors, bidirectional DC-DC converters, inverter, DC bus dynamics, BLDC motor drive, and vehicle longitudinal dynamics. These models form the analytical basis for implementing advanced control strategies aimed at energy efficiency and dynamic performance improvements in later chapters.

Chapter 3

System Modeling

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3.1 Introduction

This chapter develops a detailed, control-oriented modelling framework for the principal subsystems of the hybrid electric vehicle (HEV) powertrain. High-fidelity component models are essential for designing energy management and traction control strategies that satisfy efficiency, safety, and reliability requirements in electric vehicle applications.

The chapter first characterizes the primary energy storage devices—Lithium-ion batteries and supercapacitors—by describing their electrochemical behaviour and deriving equivalent circuit models suitable for real-time implementation. It then addresses the modelling of the power electronic interfaces, namely the bidirectional DC–DC converters and the three-phase voltage inverter used to supply the brushless DC (BLDC) motor. Average state-space models are adopted for the converters to capture their dynamic response and to facilitate digital control design.

The DC bus is subsequently modelled as the common power interface of the vehicle, with its voltage dynamics expressed through differential equations that describe the interaction between the energy sources and the traction load. Finally, the BLDC motor and the vehicle longitudinal dynamics are formulated in both electrical and mechanical domains, including torque production, speed evolution, and the effects of road slope, inertia, and resistive forces.

Altogether, this multi-domain modelling framework forms the basis for real-time simulation, hardware-in-the-loop (HIL) testing, and the development of energy management and advanced motor control strategies presented in the following chapter.

3.2 Energy Sources Modeling

This section explicitly describes the various energy sources used for traction. Each source is first described, followed by its mathematical modeling. To provide a clear understanding of how these sources are integrated within the electric vehicle architecture, a simple overview of the studied system is illustrated in Figure 3.1.

3.2.1 Battery Model

Lithium-ion batteries are widely adopted in electric vehicle (EV) applications due to their high energy density, superior power capability, and long cycle life compared with conventional electrochemical storage technologies [62]. These batteries operate through reversible lithium-ion intercalation and de-intercalation processes between the anode and cathode during charge

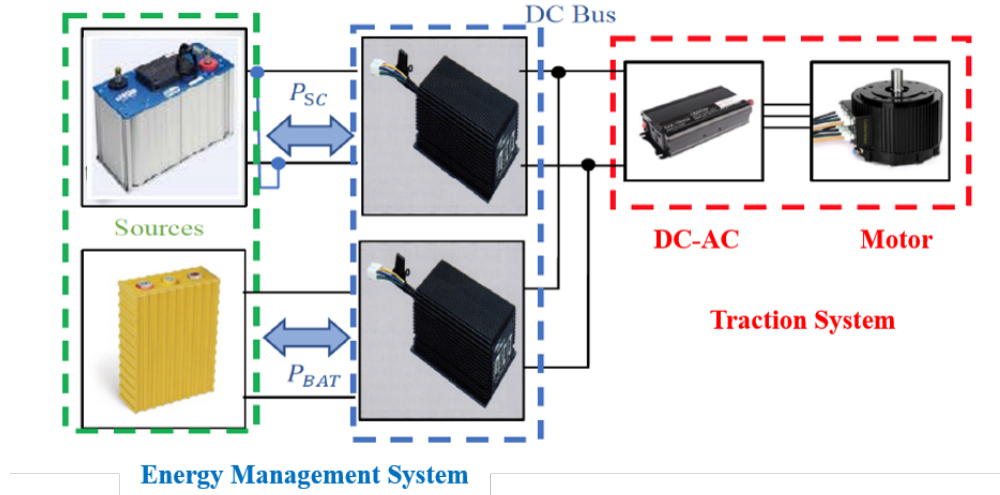


Figure 3.1: Simple overview of the studied electric vehicle system.

and discharge. Their favorable gravimetric and volumetric characteristics make them particularly suitable for traction applications, where high energy efficiency and compactness are essential [63]. Figure 3.2 illustrates the operating principle of a lithium-ion battery during charging and discharging phases.

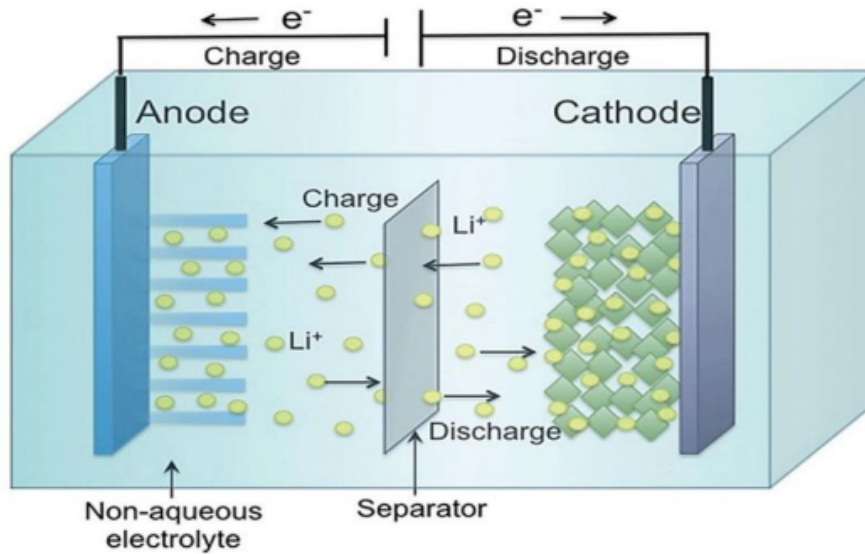


Figure 3.2: Schematic representation of a lithium-ion battery during charge and discharge.

The electrochemical behavior of a lithium-ion cell during charge and discharge can be described by the following half-cell and overall reactions. At the anode, lithium ions are

released from the graphite structure according to:



At the cathode, lithium ions are reversibly intercalated into the layered metal oxide structure, which for a typical LiCoO_2 -based chemistry can be expressed as:



Combining the two half-reactions yields the overall cell reaction governing the charge–discharge process of the lithium-ion battery:



A comparative overview of electrode materials, nominal voltages, and performance indicators for different battery technologies is provided in Table 3.1.

Table 3.1: Electrode materials and performance characteristics of different battery technologies.

Battery Type	V_{oc} (V)	Anode	Cathode	Electrolyte	Energy / Mass (Wh/kg)	Power / Mass (W/kg)
Lead–Acid	2.1	Pb	PbO_2	H_2SO_4	30–50	150–300
Nickel–Cadmium (Ni–Cd)	1.2	Cd	NiO(OH)	KOH	40–60	200–400
Nickel–Metal Hydride (NiMH)	1.23	Metal–Hydride	NiO(OH)	KOH	60–120	250–1000
Nickel–Zinc (Ni–Zn)	1.7	Zn	NiO(OH)	KOH	70–100	300–1000
Sodium–Sulfur (NaS)	2.1	Na	S	β -Alumina	150–240	150–230
Zinc–Air	1.65	Zn	O_2 (air)	KOH	300–400	100–200
Lithium–Ion (Li–ion)	3.6	Graphite	LiCoO_2 / NMC	Organic	150–250	500–2000

As summarized in Table 3.1, each battery technology presents distinct electrochemical characteristics and performance trade-offs in terms of voltage level, energy density, and power capability. Traditional technologies such as lead–acid and nickel-based batteries offer robustness and simplicity but are limited by relatively low energy density and reduced efficiency when subjected to highly dynamic operating conditions. These limitations restrict their suitability for modern electric vehicle traction systems, where compactness, high efficiency, and fast dynamic response are essential.

Lithium–ion batteries, by contrast, provide a substantially higher energy-to-mass and power-to-mass ratio, along with a higher nominal cell voltage and superior charge–discharge efficiency. These characteristics make lithium–ion technology particularly well suited for electric vehicle applications, where reducing vehicle mass, extending driving range, and supporting rapid power variations are critical requirements. Furthermore, lithium–ion batteries exhibit favorable cycling performance and compatibility with advanced power electronic converters and real-time energy management strategies.

For these reasons, lithium–ion batteries are adopted in this work as the primary energy source of the electric vehicle powertrain. Their integration enables the effective implementation of advanced control and optimization strategies developed throughout this thesis, including hybrid energy management, intelligent traction control, and power loss minimization. The selection of lithium–ion technology therefore aligns with both industrial practice and the objectives of achieving high efficiency, reliability, and scalability in modern electric vehicle systems.

1. Equivalent Circuit Modeling

For control, simulation, and energy management purposes, the lithium-ion battery is modeled using a Thévenin-based equivalent circuit, which provides a good compromise between accuracy and computational simplicity. The model consists of an open-circuit voltage source E_o in series with an internal resistance R_s , combined with one or more parallel RC networks representing polarization and diffusion phenomena. In the present study, a second-order Thevenin model is adopted, corresponding to $n = 2$ RC polarization branches, as illustrated in Figure 3.3.

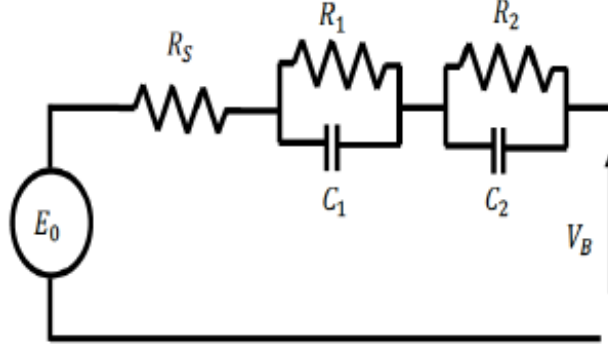


Figure 3.3: Equivalent circuit of a lithium-ion battery using a Thevenin model.

The terminal voltage of the lithium-ion battery is expressed as:

$$V_B(t) = E_o - R_s i_b(t) - V_{RC,1}(t) - V_{RC,2}(t) \quad (3.4)$$

where $i_b(t)$ is the battery current, R_s represents the ohmic resistance, and $V_{RC,k}(t)$ denotes the voltage drop across the k -th RC network associated with electrochemical polarization.

2. State of Charge Estimation

The state of charge (SOC) of the lithium-ion battery is estimated using the Coulomb counting approach, which is suitable for real-time implementation and energy management applications:

$$SOC(t) = SOC_0 - \frac{1}{C_n} \int_{t_0}^t i_b(\tau) d\tau \times 100 \quad (3.5)$$

where SOC_0 is the initial state of charge, C_n is the nominal capacity of the battery, and $i_b(t)$ is the battery current, considered positive during discharge. To improve estimation accuracy, parameters such as R_s , R_k , and C_k can be identified online using recursive identification techniques such as Recursive Least Squares (RLS) [64].

3.2.2 Supercapacitor Model

Supercapacitors (SCs) are electrochemical energy storage devices that offer significantly higher power density than conventional batteries, while exhibiting lower energy density. Their exceptional cycle life, exceeding one million charge/discharge cycles, makes them suitable for applications requiring frequent and rapid energy exchange, such as acceleration, regenerative braking, and transient power compensation in hybrid and electric vehicles [65, 66].

Unlike conventional electrolytic capacitors, SCs store energy through two complementary mechanisms: electrostatic double-layer capacitance (EDLC) and electrochemical pseudocapacitance. These processes occur at the electrode–electrolyte interface, as illustrated in Figure 3.4, highlighting the key differences between electric double-layer capacitors (EDLCs), pseudocapacitors (PCs), and hybrid supercapacitors (HSCs).

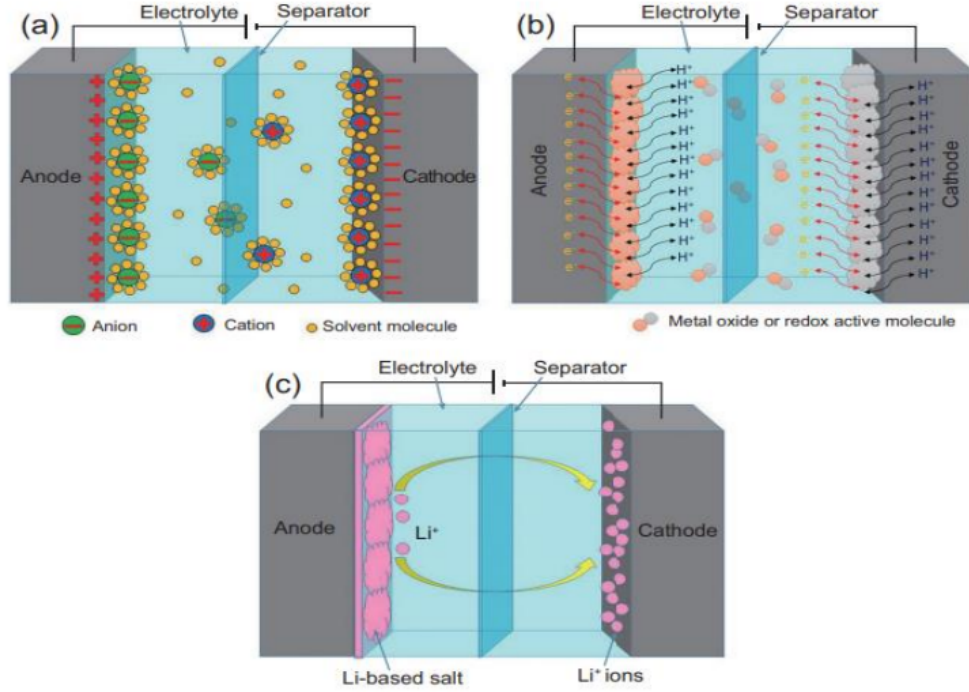


Figure 3.4: Schematic illustration of (a) electric double-layer capacitor, (b) pseudocapacitor, and (c) hybrid supercapacitor.

EDLCs store energy by electrostatic charge accumulation at the electrode surface, where ions from the electrolyte are adsorbed. In contrast, pseudocapacitors involve reversible Faradaic redox reactions, leading to higher capacitance values but lower power density. Hybrid supercapacitors (HSCs) combine both phenomena by pairing a capacitive carbon electrode with a faradaic or lithium-intercalation electrode, thus achieving a balance between energy and power densities [66].

The physical structure of an SC includes two electrodes (anode and cathode), an electrolyte, and a semipermeable separator that prevents short circuits while allowing ion transport. The electrodes are connected to current collectors that ensure efficient charge transfer during operation [65].

The equivalent circuit models (ECMs) of SCs are commonly employed for control and

system-level simulation. The simplest ECMs, shown in Figure 3.5, represent the dominant electrical behavior of SCs. The model in Figure 3.5(a) consists of a capacitance C in series with an equivalent resistance R_s , which accounts for charge and discharge losses. A slightly more accurate representation, Figure 3.5(b), adds a parallel resistance R_p to model self-discharge behavior. Multi-branch models, such as that in Figure 3.5(c), include several RC branches to capture dynamic effects but are typically reserved for high-fidelity simulations [67].

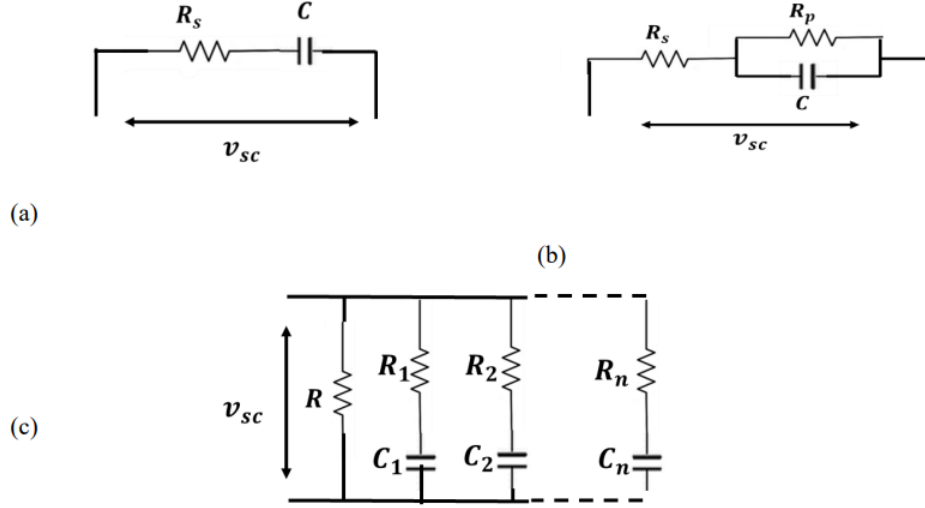


Figure 3.5: Supercapacitor ECMs: (a) simple model with equivalent series resistance, (b) model with equivalent parallel resistance, and (c) multi-branch model [67].

For control design and energy management purposes, the simplified equivalent circuit shown in Figure 3.5(a) is adopted in this work. This model consists of a capacitance C in series with an equivalent series resistance R_s , and it provides an accurate representation of the dominant electrical behavior of the supercapacitor while maintaining low computational complexity. The more detailed models in Figures 3.5(b) and (c), which include self-discharge effects and multiple dynamic branches, are primarily intended for high-fidelity electrochemical analysis and are therefore not considered here. According to the equivalent circuit of Figure 3.5(a), the voltage across the supercapacitor can be expressed as:

$$v_{sc} = R_s i_{sc} + \frac{1}{C} \int i_{sc} dt \quad (3.6)$$

where i_{sc} is the supercapacitor current, R_s is the equivalent series resistance accounting for conduction losses, and C is the capacitance. This formulation accurately captures the voltage behavior under both transient and steady-state operating conditions. Compared

with batteries, supercapacitors exhibit a nearly linear relationship between stored energy and terminal voltage, which simplifies state estimation and control design [68].

The state of charge (SOC) of the SC can thus be estimated as:

$$SOC_{sc} = \frac{v_{sc} - v_{sc,min}}{v_{sc,max} - v_{sc,min}} \quad (3.7)$$

where v_{sc} is the instantaneous terminal voltage, and $v_{sc,min}$ and $v_{sc,max}$ represent the minimum and maximum operating voltages, respectively [69].

The combination of the simplified RC model and the SOC estimation equations provides a reliable and computationally efficient framework for integrating SCs into hybrid energy management systems. These models are widely used in simulation, control design, and optimization of hybrid powertrains [67, 68].

3.3 Power Converter Modeling

To ensure bidirectional energy flow according to the adopted management strategy, current-reversible converter topologies are used.

3.3.1 DC-DC Converters Modeling

In hybrid energy storage systems (HESS), DC-DC converters play a key role in regulating energy exchange between the different energy sources and the DC bus. These converters are controlled using Pulse Width Modulation (PWM) techniques applied to IGBT switches, allowing efficient control of both output voltage and current [41].

In the proposed architecture, a battery serves as the main energy source, while a supercapacitor (SC) acts as an auxiliary unit to quickly respond to transient power demands. Both are connected to the DC bus through dedicated bidirectional buck-boost converters, which permit energy flow in both directions, ensuring reliable support during charging and discharging phases. The overall configuration of the bidirectional DC-DC converter used in this system is illustrated in Figure 3.6, which shows the two switches and inductor arrangement governing energy transfer between the source and the DC bus.

The buck-boost converter on the battery side is modeled using an average state-space approach. Considering the PWM duty cycle α_b , the converter dynamics can be expressed as:

$$L_b \cdot \frac{di_{b_mes}}{dt} = v_b - v_{dc} \cdot (1 - \alpha_b) \quad (3.8)$$

Similarly, the supercapacitor is interfaced via a buck-boost converter modeled with its own duty cycle α_{sc} . The corresponding average model is:

$$L_{sc} \cdot \frac{di_{sc_mes}}{dt} = v_{sc} - v_{dc} \cdot (1 - \alpha_{sc}) \quad (3.9)$$

These expressions describe the inductor current evolution on each side, assuming ideal switching behavior and continuous conduction mode.

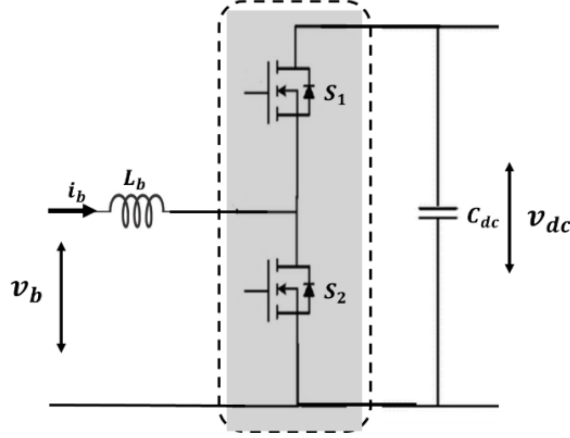


Figure 3.6: Schematic circuit of the buck-boost converter.

3.3.2 Three-Phase Voltage Inverter

The three-phase voltage source inverter (VSI) supplies the BLDC motor and is typically driven using space vector modulation (SVM) to synthesize the required phase voltages [70]. In conventional BLDC drives operating in the 120° conduction mode, only two phases are energized at any instant, which usually produces quasi-rectangular phase currents under classical commutation control. However, as demonstrated in [71], direct torque control (DTC) selects inverter switching states online to regulate torque and stator flux dynamics, which can lead to smoother current waveforms and reduced low-frequency torque ripple compared with conventional approaches.

The inverter consists of three legs, each composed of an upper and a lower IGBT (with anti-parallel diodes), as shown in Figure 3.7. For phase $x \in \{a, b, c\}$, the binary gating signals are denoted by S_x for the upper switch and $\bar{S}_x$ for the lower switch. Under ideal complementary operation (neglecting dead-time and shoot-through protection), the leg commands satisfy:

$$\bar{S}_x = 1 - S_x, \quad S_x \in \{0, 1\}. \quad (3.10)$$

Thus, $S_x = 1$ indicates that the upper device of leg x is ON (and the lower is OFF), whereas $S_x = 0$ indicates that the lower device is ON (and the upper is OFF). With this definition, the pole (phase-to-negative-bus) voltages are expressed as:

$$\begin{cases} V_{aN} = S_a V_{DC} \\ V_{bN} = S_b V_{DC} \\ V_{cN} = S_c V_{DC} \end{cases} \quad (3.11)$$

where V_{DC} is the DC-link voltage.

The corresponding line-to-line voltages applied to the motor terminals are then given by:

$$\begin{cases} V_{ab} = V_{aN} - V_{bN} = V_{DC}(S_a - S_b) \\ V_{bc} = V_{bN} - V_{cN} = V_{DC}(S_b - S_c) \\ V_{ca} = V_{cN} - V_{aN} = V_{DC}(S_c - S_a) \end{cases} \quad (3.12)$$

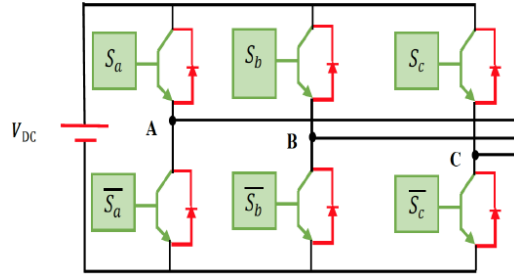


Figure 3.7: Equivalent circuit of a two-level three-phase voltage inverter.

3.4 DC Bus Model

In electric vehicle powertrains, the DC bus serves as a common energy coupling interface between the energy sources and the traction system. It enables continuous power exchange while decoupling the dynamics of the storage elements from those of the motor drive. Maintaining a stable DC bus voltage is essential to ensure proper operation of the inverter and to guarantee reliable torque and speed control of the BLDC motor.

As illustrated in Figure 3.8, the DC bus is modeled as a capacitive energy buffer represented by the DC-link capacitor C_{dc} . This capacitor absorbs power fluctuations caused by load transients and switching actions, thereby smoothing the DC voltage and improving

overall system stability. The currents injected into the DC bus originate from the battery (i_b) and the supercapacitor (i_{sc}), while the traction system draws the load current i_l .

Neglecting leakage effects and parasitic resistances, which are typically small and have a negligible impact on the voltage dynamics over the operating time scales considered in this work, the DC bus behavior is governed by the capacitor current balance. The dynamic equation of the DC bus voltage V_{dc} is thus expressed as:

$$C_{dc} \frac{dV_{dc}}{dt} = i_b + i_{sc} - i_l \quad (3.13)$$

This formulation highlights the fundamental role of the DC-link capacitor as an energy buffer: any imbalance between the supplied currents ($i_b + i_{sc}$) and the load demand (i_l) results in a corresponding variation of the DC bus voltage. Consequently, regulating the DC bus voltage amounts to controlling the net current injected into the capacitor.

The simplified capacitive DC bus model adopted in this work offers a clear physical interpretation and is well suited for control design and energy management purposes. It is widely used in hybrid energy storage systems and traction applications, where voltage regulation is achieved through coordinated control of the source-side converters rather than through passive damping elements.

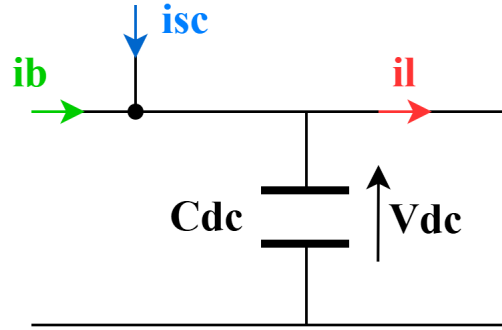


Figure 3.8: Equivalent electrical model of the DC bus.

3.5 Traction System Modeling

The traction system constitutes the core of the electric vehicle powertrain, as it directly converts electrical energy into mechanical motion at the wheels. In this work, the traction subsystem is modeled using a brushless DC (BLDC) motor mechanically coupled to a direct current (DC) machine, which is employed as a controllable load to emulate vehicle resistance

and braking conditions. This configuration allows realistic reproduction of traction and regenerative operating modes within both simulation and experimental environments.

3.5.1 BLDC Motor Modeling

BLDC motors are widely employed in electric vehicle traction systems due to their high efficiency, compact structure, and superior torque-to-weight ratio. The BLDC motor combines the structural simplicity of a DC machine with the control advantages of an AC drive, featuring a permanent magnet rotor and electronically commutated stator currents. Its electromagnetic behaviour can be represented by electrical, mechanical, and electromagnetic equations that describe voltage balance, torque production, and motion dynamics [72].

The model adopted in this work is organized into four parts:

1. Electrical model

The stator of a three-phase BLDC motor consists of three Y-connected windings displaced by 120° electrical. Neglecting mutual coupling and assuming equal resistance and inductance for each phase, the voltage equations of the stator windings are expressed as

$$\begin{cases} v_{ab} = R(i_a - i_b) + (L - M)\frac{d(i_a - i_b)}{dt} + e_a - e_b \\ v_{bc} = R(i_b - i_c) + (L - M)\frac{d(i_b - i_c)}{dt} + e_b - e_c \\ v_{ca} = R(i_c - i_a) + (L - M)\frac{d(i_c - i_a)}{dt} + e_c - e_a \end{cases} \quad (3.14)$$

where v_{ab}, v_{bc}, v_{ca} are the line-to-line voltages, i_a, i_b, i_c the phase currents, e_a, e_b, e_c the back electromotive forces (back-EMFs), R the phase resistance, and L and M the self- and mutual inductances, respectively.

The back-EMFs are trapezoidal in shape and depend on the rotor electrical position θ_e as:

$$e_k = \frac{K_e}{2} \omega_m F\left(\theta_e - \frac{2\pi(k-1)}{3}\right), \quad k = a, b, c \quad (3.15)$$

where K_e is the back-EMF constant, ω_m is the rotor speed, and $F(\theta_e)$ denotes the normalised trapezoidal back-EMF function.

While the back-EMF profile remains trapezoidal, the phase current waveform depends on the control strategy. In traditional two-phase conduction mode, the current is also shaped trapezoidally to align with the flat-top EMF segments, enabling efficient torque generation. With sinusoidal modulation or field-oriented control (FOC), the

same BLDC motor can be driven with sinusoidal currents, acting like the PMSM behaviour for smoother torque and reduced harmonics. This flexibility enables dual-mode operation, adapting the motor drive to different performance or efficiency targets. Figure 3.9 illustrates this distinction, comparing classical BLDC drive operation (left) with sinusoidal current injection (right), both under trapezoidal EMF excitation.

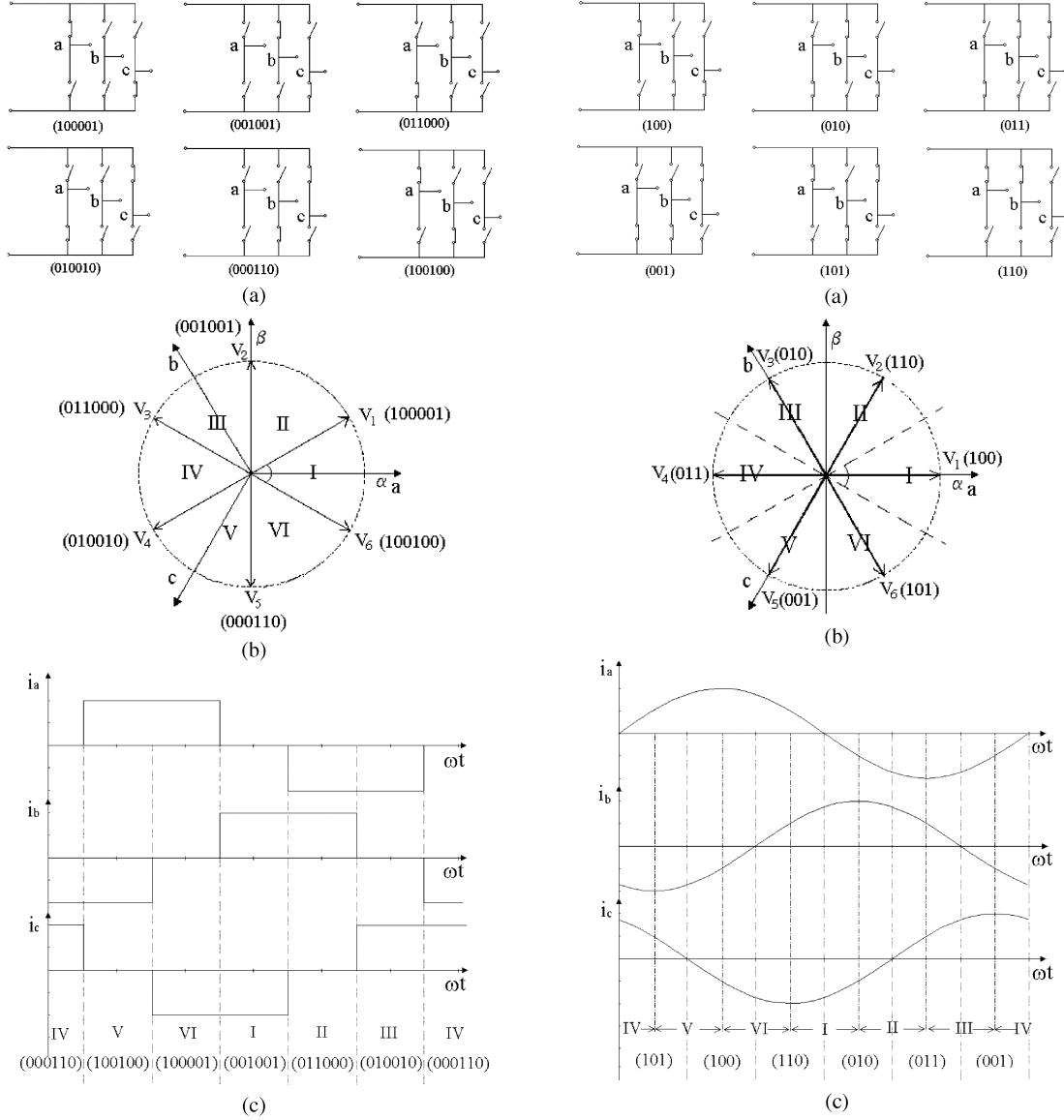


Figure 3.9: Nonzero-voltage space vectors for the BLDC drive.

2. Electromagnetic torque and mechanical dynamics

The electromagnetic torque generated by the interaction between stator currents and

rotor magnetic fields is defined as:

$$T_e = \frac{K_t}{2} \left[F(\theta_e) i_a + F(\theta_e - \frac{2\pi}{3}) i_b + F(\theta_e - \frac{4\pi}{3}) i_c \right] \quad (3.16)$$

where K_t is the torque constant. The mechanical dynamics of the motor, including friction and load torque effects, are governed by

$$J \frac{d\omega_m}{dt} + B_v \omega_m = T_e - T_L \quad (3.17)$$

where J is the rotor inertia, B_v the viscous friction coefficient, and T_L the load torque applied to the motor shaft.

3. Equivalent circuit representation

Under the two-phase conduction mode—where at any instant two phases conduct current while the third remains open—the motor can be represented by the equivalent circuit shown in Figure 3.10. This circuit illustrates the electrical coupling of the stator windings and the corresponding back-EMFs.

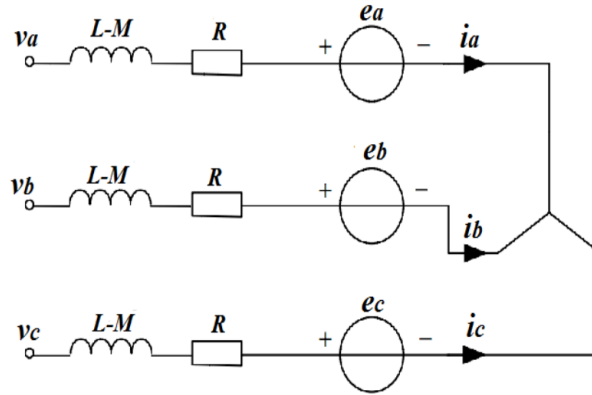


Figure 3.10: Equivalent circuit of a three-phase BLDC motor under two-phase conduction.

4. State-space representation

The state-space approach is a fundamental tool in modern control theory for modelling and analysing dynamic systems [72]. In this work, the BLDC motor controlled by a full-bridge inverter operating in two-phase conduction mode is described by the following state-space model:

$$\begin{bmatrix} \dot{i}_a \\ \dot{i}_b \\ \dot{\omega} \\ \dot{\theta}_s \end{bmatrix} = \begin{bmatrix} -\frac{R}{L} & 0 & 0 & 0 \\ 0 & -\frac{R}{L} & 0 & 0 \\ 0 & 0 & -\frac{B}{J} & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ \omega \\ \theta_s \end{bmatrix} + \begin{bmatrix} \frac{2}{3L} & \frac{1}{3L} & 0 \\ -\frac{1}{3L} & \frac{1}{3L} & 0 \\ 0 & 0 & \frac{1}{J} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u_{ab} - e_{ab} \\ u_{bc} - e_{bc} \\ T_e - T_L \end{bmatrix} \quad (3.18)$$

where u_{ab} and u_{bc} are the line voltages, e_{ab} and e_{bc} the back-EMFs, R the phase resistance, L the phase inductance, J the rotor moment of inertia, B the friction coefficient, T_e the electromagnetic torque, T_L the load torque, ω the rotor speed, θ_s the rotor position, and i_a and i_b the phase currents.

To facilitate control implementation, the Clarke transformation maps the three-phase (a, b, c) variables into the two-phase (α, β) stationary frame:

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & \frac{\sqrt{3}}{3} & -\frac{\sqrt{3}}{3} \end{bmatrix} \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix}, \quad \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & \frac{\sqrt{3}}{3} & -\frac{\sqrt{3}}{3} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \quad (3.19)$$

The flux linkages in the $\alpha\beta$ frame are given by

$$\lambda_\alpha = \int (V_\alpha - Ri_\alpha) dt, \quad \lambda_\beta = \int (V_\beta - Ri_\beta) dt \quad (3.20)$$

with the estimated flux magnitude

$$\phi_s = \sqrt{\lambda_\alpha^2 + \lambda_\beta^2}. \quad (3.21)$$

The electromagnetic torque can then be expressed as

$$T_e = \frac{3}{2}P(\lambda_\alpha i_\beta - \lambda_\beta i_\alpha) \quad (3.22)$$

where P is the number of pole pairs. The motor parameters used in this study are listed in [Appendix](#).

The presented BLDC motor model integrates the electrical, mechanical, and electromagnetic dynamics necessary for realistic simulation and control design. By combining a trapezoidal back-EMF representation with Clarke-transformed variables, the model enables accurate torque and flux estimation and provides a robust analytical basis for control strategies such as direct torque control (DTC) and field-oriented control (FOC), depending on the employed commutation method.

3.5.2 Vehicle Dynamics Model

The longitudinal motion of a vehicle, particularly on an incline, is governed by the balance between the traction forces generated by the powertrain and the forces resisting motion.

According to Newton's second law, the net force acting on the vehicle determines its acceleration. By including both translational and equivalent rotational inertia, this relationship can be written as:

$$\gamma M \frac{dv}{dt} = \sum_{i=1}^n F_i - F_r \quad (3.23)$$

where γ is a correction factor accounting for the rotational inertia of components such as wheels and drive shafts, M is the vehicle mass, v is its longitudinal velocity, F_i represents the individual traction forces, and F_r is the total resistive force acting on the vehicle [73]. Figure 3.11 illustrates the main forces acting on a vehicle travelling on an inclined road.

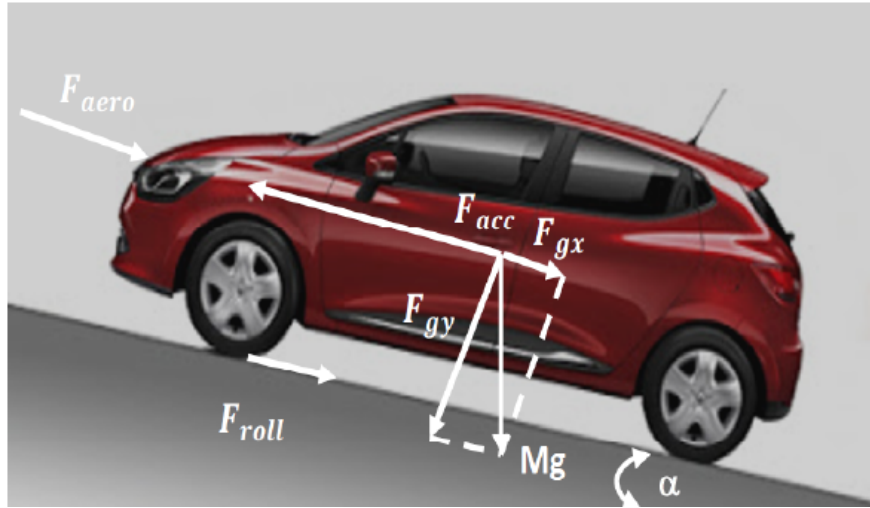


Figure 3.11: Schematic representation of the forces acting on a vehicle moving on an incline.

The total resistive force F_r is the sum of three contributions. *Rolling resistance* F_{roll} arises mainly from the deformation of the tyres and the road surface. It is modelled as:

$$F_{\text{roll}} = Mg\mu \cos \alpha \quad (3.24)$$

where μ is the rolling resistance coefficient, g is the gravitational acceleration, and α is the road slope angle [74].

Aerodynamic drag F_{aero} is determined by the vehicle geometry and the relative air speed, and is expressed as:

$$F_{\text{aero}} = \frac{1}{2} \rho_{\text{air}} S C_d (v + v_w)^2 \quad (3.25)$$

where ρ_{air} is the air density, S is the frontal area of the vehicle, C_d is the drag coefficient, and v_w is the wind speed relative to the vehicle [75].

Gravitational component F_{pente} corresponds to the component of the vehicle weight acting along the slope:

$$F_{\text{pente}} = Mg \sin \alpha \quad (3.26)$$

The overall resistive force is therefore given by:

$$F_{\text{resist}}(v) = F_{\text{roll}} + F_{\text{aero}} + F_{\text{pente}} \quad (3.27)$$

Under steady-state conditions, where the acceleration term dv/dt is zero, the traction force equals the total resistive force. The mechanical power required to maintain a constant speed v is then:

$$P_{\text{resist}}(v) = F_{\text{resist}}(v) v \quad (3.28)$$

For operation on flat roads (negligible slope, $\alpha \approx 0$), the power demand can be approximated by:

$$P_{\text{req}} = K_{\text{aero}} v^3 + K_f v \quad (3.29)$$

where K_{aero} and K_f are aggregated coefficients representing the aerodynamic drag and rolling resistance contributions, respectively. This formulation is used for powertrain sizing and for developing energy management strategies aimed at reducing the vehicle's energy consumption.

3.6 Conclusion

This chapter has developed control-oriented models for the main components of the hybrid electric vehicle powertrain. The formulation covers the lithium-ion battery and supercapacitor as hybrid energy storage units, the bidirectional DC–DC converters used for power interfacing, the shared DC bus, and the BLDC motor integrated with vehicle longitudinal dynamics.

Each subsystem was described by differential equations and average state-space representations in order to capture its dominant dynamics while remaining suitable for embedded implementation. Bidirectional power flow, current dynamics, and the coupling between electrical and mechanical domains were explicitly taken into account so that the resulting models reflect realistic operating conditions.

The complete model set constitutes the analytical basis for the synthesis, tuning, and validation of energy management and motor control algorithms. The next chapter 4 builds upon these developments to design an advanced energy management system (EMS), incorporating fractional-order PI (FOPI) controllers for speed regulation, metaheuristic optimization (PSO, GWO, and BCO) for offline parameter tuning, and a hybrid fuzzy–PSO strategy for real-time adaptive control. These control solutions are integrated into the traction subsystem and evaluated under dynamic driving conditions to assess their effectiveness in practical scenarios.

Chapter 4

Description of the Proposed Strategies

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4.1 Introduction

This chapter presents the design and implementation of the control and energy management strategies for a hybrid electric vehicle (HEV) incorporating with a hybrid energy storage system (HESS) consisting of a lithium-ion battery and a supercapacitor. The developments build directly on the component models formulated in Chapter 3 and extend them toward complete supervisory and traction control structures.

On the power sources side, an energy management system (EMS) is formulated on the basis of frequency separation and Lyapunov-based regulation. The EMS allocates the power demand between the battery and the supercapacitor and ensures the stabilization of the DC bus voltage under variable operating conditions. On the traction side, the BLDC motor is driven by a direct torque control (DTC) scheme, combined with an advanced speed controller based on a fractional-order PI (FOPI) structure and an adaptive flux controller dedicated to loss minimization.

The chapter then recalls the main principles of fractional-order calculus and fractional-order PI/PID controllers, with emphasis on the FOPI control law and tuning techniques suitable for electric-drive applications. These concepts provide the theoretical background required for the subsequent controller synthesis.

Metaheuristic optimization algorithms such as Particle Swarm Optimization (PSO), Bee Colony Optimization (BCO), and Grey Wolf Optimizer (GWO), are subsequently introduced and used to perform offline tuning of the FOPI parameters according to performance indices such as IAE and ITAE.

Finally, a hybrid Fuzzy–PSO self-tuning FOPI controller for real-time speed regulation in EV drives is proposed. In this architecture, fuzzy logic adapts the fractional order, whereas PSO updates the proportional and integral parameters online.

The structure of the chapter is organized as follows. Section 4.2 describes the adopted HEV topology. Section 4.3 details the control strategy on the power-source side, including DC-bus regulation and frequency separation. Section 4.4 introduces the traction-side strategies based on DTC and advanced controllers. Sections 4.5–4.7 present the fractional-order control framework and the metaheuristic-based offline tuning of the FOPI controller. Sections 4.8 and 4.9 describe the hybrid Fuzzy–PSO self-tuning FOPI controller and its design procedure.

4.2 Description of the Used Topology

The proposed hybrid electric vehicle (HEV) powertrain topology integrates two tightly coupled functional subsystems: the **Energy Management System (EMS)** and the **Traction System**. This dual-structure design ensures efficient power allocation, optimized motor control, and improved vehicle performance under dynamic driving conditions.

As illustrated in Figure 4.1, the energy source subsystem is composed of a hybrid energy storage system (HESS) that couples a lithium-ion battery and a supercapacitor (SC). These storage elements are interfaced with a common DC-link via two independent bidirectional DC-DC converters, enabling controlled energy exchange in both charging and discharging modes.

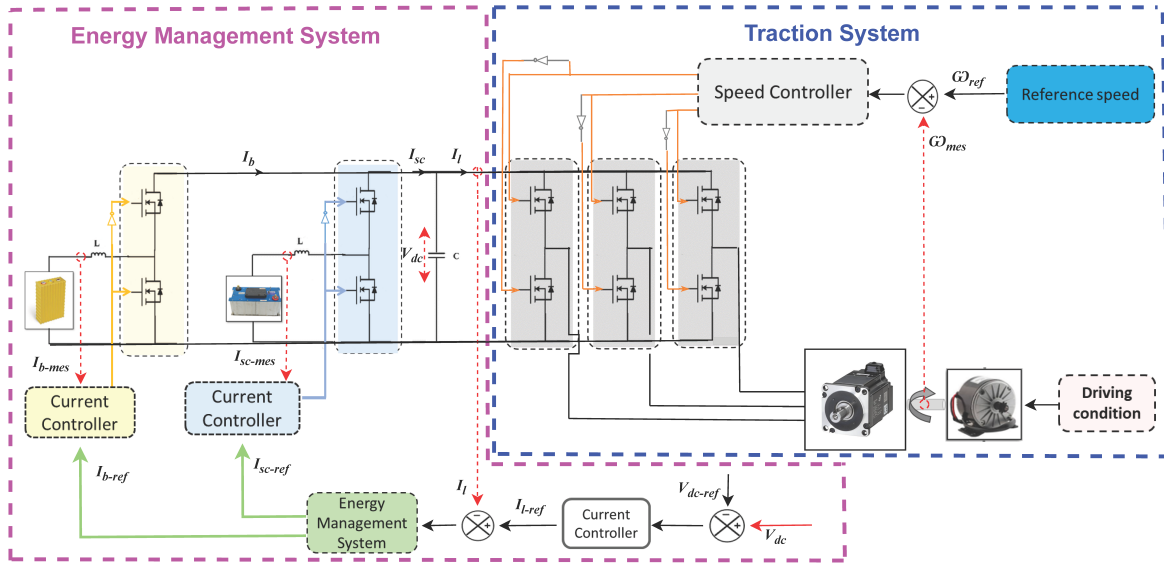


Figure 4.1: Overall architecture of the hybrid electric vehicle, showing energy management and traction subsystems.

The EMS incorporates a dedicated energy management algorithm that analyzes the load power demand and determines the optimal current references for each source. The battery supplies the low-frequency component of the load current, while the supercapacitor handles high-frequency transients. This decomposition is based on filtering the total current using a low-pass and high-pass filter pair.

Three current controllers are employed to regulate:

- the battery current I_b
- the supercapacitor current I_{sc}

- and the overall bus current I_l according to the reference V_{dc_ref}

This hybrid architecture improves power distribution and enhances energy efficiency. On the traction side, the regulated DC bus supplies a three-phase inverter driving a BLDC motor. The motor speed is regulated by a dedicated controller to match the reference ω_{ref} , which is derived from the current driving condition.

4.3 Control Strategy Used in Power Sources Side

The energy management subsystem is responsible for real-time power balancing and DC bus voltage stabilization. It integrates two complementary control functions: one for DC bus regulation and the other for power-sharing via frequency separation. The complete control architecture is presented in Figure 4.2.

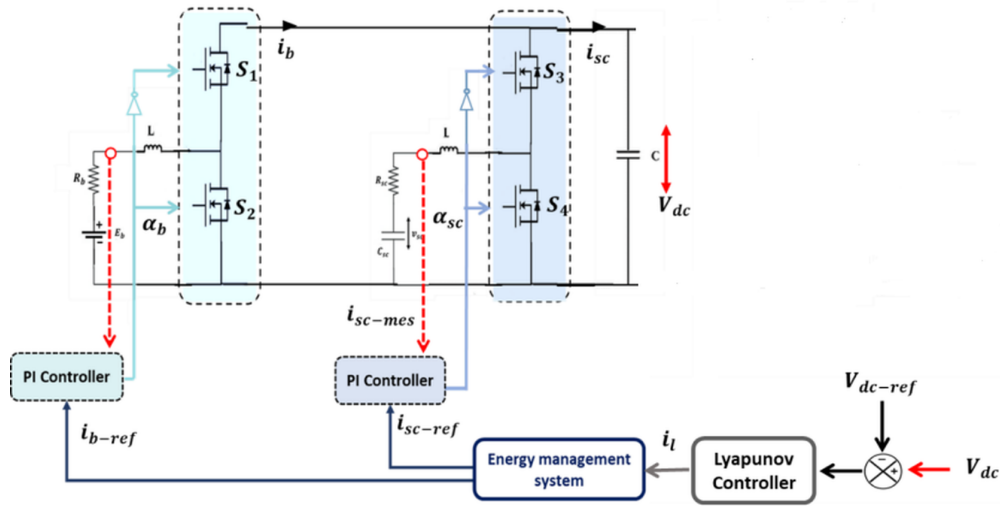


Figure 4.2: Power source control architecture with energy management system.

4.3.1 DC Bus Voltage Control

The DC bus voltage V_{dc} plays a central role in maintaining the stability and power quality of the entire hybrid energy system. Any deviation in the DC bus voltage directly affects the performance of the traction inverter and may lead to degraded motor operation or component stress. Consequently, a robust regulation strategy is required to ensure that V_{dc} remains tightly controlled despite disturbances caused by load variations and energy-source dynamics.

The DC-link dynamics are governed by the balance between the injected power from the energy sources and the power drawn by the load. This behaviour can be expressed in a general nonlinear form as:

$$\frac{dV_{dc}}{dt} = f(V_{dc}, I_{sc}, I_{bat}, P_{load}) \quad (4.1)$$

where I_{sc} and I_{bat} represent the supercapacitor and battery currents, respectively, and P_{load} denotes the instantaneous load power. This nonlinear coupling highlights the need for a control law capable of ensuring voltage stability under simultaneous fluctuations in energy supply and demand.

To guarantee closed-loop stability, a Lyapunov-based control approach is adopted. The voltage tracking error is defined as:

$$e_v = V_{dc} - V_{dc}^{ref} \quad (4.2)$$

and a positive definite Lyapunov candidate function is selected as:

$$V_L = \frac{1}{2}e_v^2 \quad (4.3)$$

The time derivative of the Lyapunov function along the system trajectory is given by:

$$\dot{V}_L = e_v \cdot \frac{dV_{dc}}{dt} \quad (4.4)$$

The control objective is to enforce a negative definite Lyapunov derivative, i.e., $\dot{V}_L \leq 0$, which guarantees asymptotic convergence of the DC bus voltage to its reference value. This is achieved by adjusting the duty ratios of the bidirectional DC–DC converters connected to the battery and supercapacitor. These control actions regulate the energy flow into the DC bus in real time, compensating for disturbances introduced by load transients and power imbalance.

By construction, the Lyapunov-based controller ensures global stability of the voltage regulation loop while preserving robustness against system nonlinearities and uncertainties. In addition, this formulation provides a systematic framework for shaping the convergence rate and damping behaviour of the DC voltage dynamics. As a result, voltage ripple is minimized and safe operating conditions for downstream components, such as the inverter and motor drive, are maintained under all operating modes.

4.3.2 Frequency Separation for Energy Management System

The proposed Energy Management System (EMS) is based on a frequency separation strategy inspired by [76], applied to a hybrid battery–supercapacitor energy storage architecture. The main objective is to exploit the complementary characteristics of the two sources: the battery, characterized by high energy density, supplies the average (slow-varying) power demand, while the supercapacitor, characterized by high power density and fast dynamics, compensates rapid transient power components. This approach improves overall energy efficiency, reduces battery current stress, and contributes to extending battery lifetime.

1. Power Decomposition by Frequency Separation

The traction power demand is decomposed into low- and high-frequency components according to:

$$P_{load}(t) = P_{low}(t) + P_{high}(t) \quad (4.5)$$

A low-pass filter is used to extract the slow-varying component:

$$P_{low}(s) = H_{LPF}(s) P_{load}(s) \quad (4.6)$$

while the high-frequency component is obtained as:

$$P_{high}(s) = P_{load}(s) - P_{low}(s) \quad (4.7)$$

The low-frequency power component is assigned to the battery, whereas the high-frequency component is allocated to the supercapacitor. This separation prevents the battery from supplying rapid power fluctuations and allows the supercapacitor to absorb transient loads efficiently.

2. Conversion of Power Components into Current References

The separated power components are converted into current references using the DC-link voltage:

$$I_{batt_ref}(t) = \frac{P_{low}(t)}{V_{dc}(t)}, \quad I_{sc_ref}(t) = \frac{P_{high}(t)}{V_{dc}(t)} \quad (4.8)$$

These current references define the desired contributions of the battery and the supercapacitor to the DC-bus current and serve as setpoints for the inner current control loops.

3. Current Loop Modeling and PI Controller Design

Although the battery is modeled using a second-order Thévenin equivalent circuit to represent electrochemical and voltage dynamics at the system level, the design of the inner current control loops relies on a control-oriented averaged model of the bidirectional DC–DC converters. At this control level, the dominant dynamics are governed by the converter inductance and series resistance, while battery polarization effects evolve on a much slower time scale and are therefore neglected for current controller synthesis. Based on the averaged converter model presented in [76], the current dynamics of the battery and supercapacitor branches are described by:

$$L_{batt} \frac{di_{batt}}{dt} = V_{batt} - V_{dc}(1 - \alpha_{batt}) - R_{batt}i_{batt} \quad (4.9)$$

$$L_{sc} \frac{di_{sc}}{dt} = V_{sc} - V_{dc}(1 - \alpha_{sc}) - R_{sc}i_{sc} \quad (4.10)$$

where α_{batt} and α_{sc} are the duty cycles of the bidirectional DC–DC converters.

Linearization around an operating point yields first-order transfer functions:

$$H_{batt}(s) = \frac{i_{batt}(s)}{\alpha_{batt}(s)} = \frac{-K}{L_{batt}s + R_{batt}} \quad (4.11)$$

$$H_{sc}(s) = \frac{i_{sc}(s)}{\alpha_{sc}(s)} = \frac{-K}{L_{sc}s + R_{sc}} \quad (4.12)$$

PI controllers are employed to regulate the source currents:

$$H_{PI}(s) = K_p \left(1 + \frac{1}{T_i s} \right) \quad (4.13)$$

The controller parameters are selected to achieve a desired closed-loop second-order response:

$$H_{cl}(s) = \frac{1}{T_0^2 s^2 + 2\xi T_0 s + 1} \quad (4.14)$$

where T_0 denotes the targeted time constant and ξ is the damping ratio ensuring a non-oscillatory response.

In accordance with hierarchical control principles, the inner current loops are tuned significantly faster than the outer EMS dynamics, guaranteeing accurate tracking of current references and stable interaction between the energy sources.

4. Complete EMS Structure

The complete EMS architecture based on frequency separation is illustrated in Fig. 4.3. The low-pass and high-pass filters generate the battery and supercapacitor current references,

respectively, while independent PI controllers regulate the corresponding DC–DC converters. This structure ensures smooth power sharing, reduced DC-bus current ripple, improved transient response, and enhanced battery lifetime.

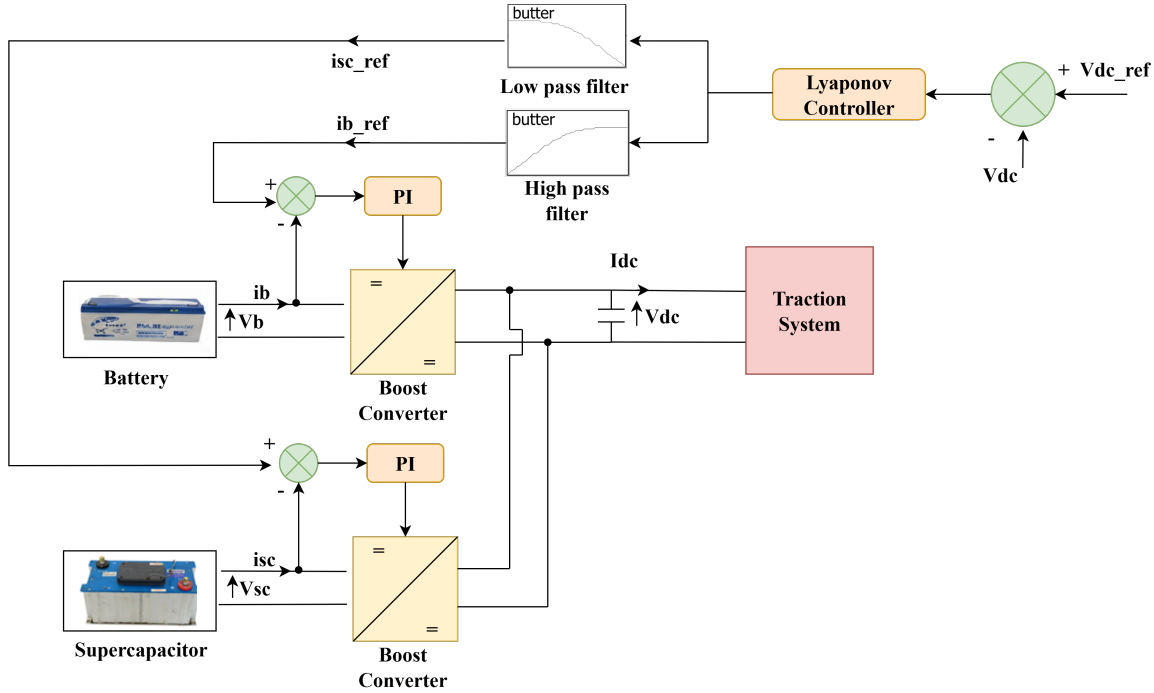


Figure 4.3: Control diagram of the energy management system based on frequency separation.

4.4 Proposed Strategies Used in Traction System Side

The traction control system represents the principal focus of this thesis, as it directly governs the dynamic behaviour and energy efficiency of the electric vehicle powertrain. In this work, a new control architecture is developed to enhance the performance of the BLDC motor by introducing two complementary strategies that constitute the core contribution of the thesis. The first strategy concerns the speed regulation loop, where an advanced hybrid controller, combining fractional-order PI control with a real-time tuning through metaheuristics and fuzzy logic—is proposed to improve adaptability under varying operating conditions. The second strategy introduces a new adaptive flux control algorithm based on fuzzy logic and incremental conductance, specifically designed to adjust the stator flux in real time with the objective of reducing electromagnetic power losses. These two controllers operate jointly within the proposed DTC-based traction framework, providing a more efficient control of the BLDC motor. The complete traction control structure is illustrated in Figure 4.4, which

highlights the integration of the optimized FOPI controller and the adaptive flux regulation module within the overall DTC architecture.

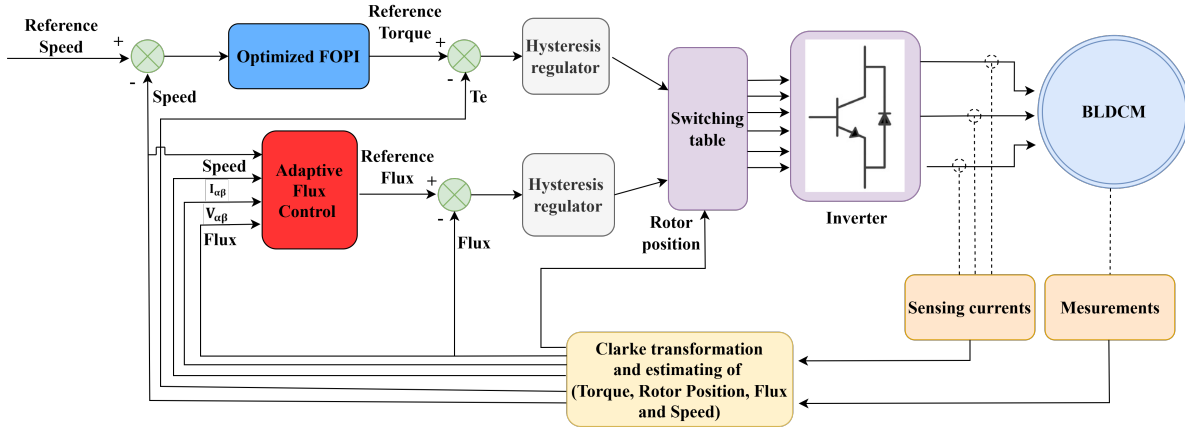


Figure 4.4: Traction system control architecture integrating DTC.

4.4.1 Speed Control via Direct Torque Control

The Direct Torque Control (DTC) approach provides fast dynamic response by regulating the motor's torque and stator flux. It relies on the real-time estimation of electromagnetic torque and flux linkage. These variables are used by hysteresis comparators and a voltage vector switching table, which is presented in Table 4.1 to modulate the inverter outputs. The system sectors and back-EMF characteristics are shown in Figure 4.5.

Table 4.1: Switching table for the DTC of the BLDC Drive.

Torque τ	Flux ϕ	Sector					
		I	II	III	IV	V	VI
1	1	V1	V2	V3	V4	V5	V6
	0	V2	V3	V4	V5	V6	V1
	-1	V3	V4	V5	V6	V1	V2
-1	1	V1	V2	V3	V4	V5	V6
	0	V0	V0	V0	V0	V0	V0
	-1	V3	V4	V5	V6	V1	V2

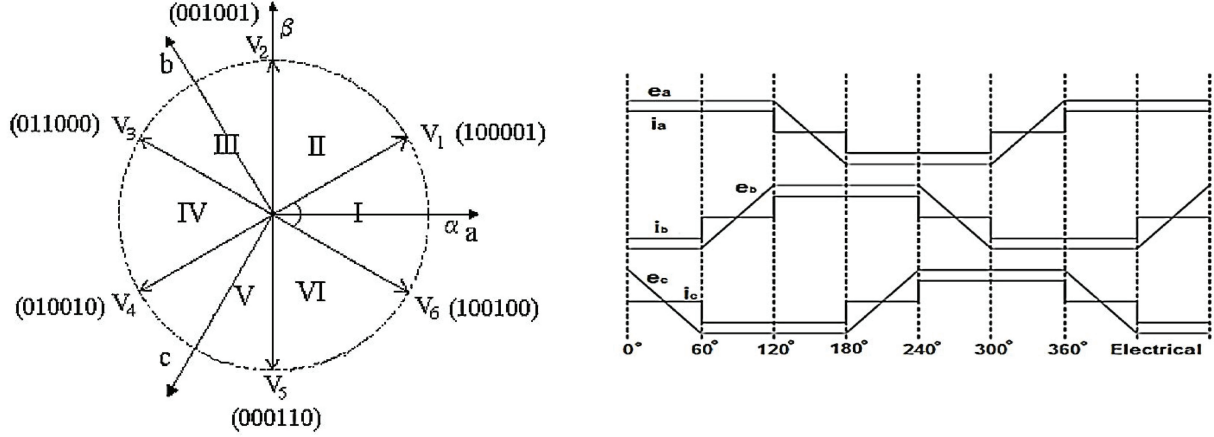


Figure 4.5: Sectors of voltage vector in Left and Back-EMFs with phases currents in Right.

This approach eliminates the need for coordinate transformation or PWM generation, thus simplifying implementation and enhancing torque precision.

4.4.2 The Proposed Advanced Controllers

Two new control strategies are proposed to enhance system adaptability and energy efficiency. These correspond to the blue and red blocks in Figure 4.4.

1. Optimized FOPI Controller for Adaptive Speed Control

The blue-colored block in the DTC control scheme represents the proposed FOPI controller for adaptive speed regulation. It generalizes the classical PI controller by incorporating a fractional-order integrator of order λ , as shown in the equation below:

$$u(t) = K_p e(t) + K_i D^{-\lambda} e(t) \quad (4.15)$$

Tuning is performed as follows:

- **Offline Optimization:** Parameters K_p , K_i , and λ are optimized using PSO, BCO, and GWO with objective functions such as ITAE and IAE.
- **Online Hybrid Tuning:** A fuzzy logic framework dynamically adapts λ based on operating conditions, while PSO optimizes the parameters K_p and K_i in real time.

This adaptive FOPI controller is described in detail in the following sections and validated in both HIL and a real test bench will be presented in Chapter 5.

2. Adaptive Flux Control for Power Loss Minimization

The red-colored block in Figure 4.4 represents the second strategy: adaptive stator flux regulation. It aims to minimize copper and iron losses under variable load and speed conditions using:

- **Incremental Conductance-Based Flux Adjustment:** This method continuously tracks the optimal flux reference by adjusting it based on the incremental change in conductance, thereby reducing power losses.
- **Fuzzy Logic-Based Flux Controller:** A rule-based fuzzy system evaluates real-time speed and load inputs to adaptively modify the flux reference for improved efficiency.

Both controllers are integrated within the DTC framework and validated experimentally via HIL in Chapter 6, demonstrating significant improvements in efficiency behavior.

4.5 Fractional-Order Calculus in Control Theory

Fractional-order calculus (FOCS) extends the concepts of classical integer-order differentiation and integration to non-integer orders. This generalization enables more accurate modelling of systems with memory and hereditary properties. Two commonly used definitions in FOCS are the Riemann–Liouville and Caputo derivatives.

The Riemann–Liouville fractional derivative of order α is defined as

$$D^\alpha f(t) = \frac{1}{\Gamma(n - \alpha)} \frac{d^n}{dt^n} \int_0^t \frac{f(\tau)}{(t - \tau)^{\alpha - n + 1}} d\tau \quad (4.16)$$

where $n - 1 < \alpha < n$, $n \in \mathbb{N}$, and $\Gamma(\cdot)$ denotes the gamma function.

The Caputo fractional derivative of the same order is given by

$$D^\alpha f(t) = \frac{1}{\Gamma(n - \alpha)} \int_0^t \frac{f^{(n)}(\tau)}{(t - \tau)^{\alpha - n + 1}} d\tau \quad (4.17)$$

In control applications, the Caputo definition is generally preferred because it allows the use of standard (integer-order) initial conditions together with fractional dynamics [77]. In the context of control theory, fractional-order models and operators are particularly useful for:

- accurately representing systems with distributed parameters, such as viscoelastic materials, electrochemical cells, and biological tissues [78];

- increasing the robustness and adaptability of control systems via additional fractional-order parameters [79];
- capturing memory effects and anomalous diffusion phenomena that are important in heat transfer and battery dynamics [80].

These properties motivate the introduction of fractional-order controllers, and in particular fractional-order PID and PI structures, in advanced control schemes.

4.5.1 Fractional-Order PID Controllers Design

Fractional-order PID (FOPID or $PI^\lambda D^\mu$) controllers generalize classical PID structures by introducing two additional tuning parameters: λ (the order of integration) and μ (the order of differentiation). The controller transfer function in the Laplace domain can be written as:

$$G_c(s) = K_p + \frac{K_i}{s^\lambda} + K_d s^\mu; \quad \lambda, \mu \in R^+ \quad (4.18)$$

where K_p , K_i , and K_d denote the proportional, integral, and derivative gains, respectively.

Compared with conventional integer-order PID controllers, FOPID controllers offer several advantages:

- they provide greater tuning flexibility through the five design parameters K_p , K_i , K_d , λ , and μ [77];
- they can deliver improved performance in controlling fractional-order or highly complex systems, such as thermal processes and robotic actuators [78];
- they exhibit enhanced robustness with respect to parameter variations and external disturbances [81].

In the time domain, the corresponding control law associated with the FOPID structure can be expressed as:

$$u(t) = K_p e(t) + K_i D^{-\lambda} e(t) + K_d D^\mu e(t) \quad (4.19)$$

where $e(t)$ is the tracking error and $D^{-\lambda}$ and D^μ denote the fractional integral and derivative operators, respectively.

4.5.2 Fractional-Order PI Controller Design

The fractional-order PI (FOPI) controller, originally introduced by Podlubny in the context of fractional-order systems [77], is a special case of the FOPID controller in which the derivative term is omitted. The integer-order integrator of a conventional PI controller is replaced by a fractional-order operator, yielding an additional tuning degree of freedom. The FOPI control law is defined as:

$$u(t) = K_p e(t) + K_i D^{-\lambda} e(t) \quad (4.20)$$

where K_p and K_i denote the proportional and integral gains, λ is the fractional integrator order, and $e(t)$ is the control error. In general, the error signal can be written as:

$$e(t) = X_{\text{ref}}(t) - X(t) \quad (4.21)$$

with $X_{\text{ref}}(t)$ the reference signal and $X(t)$ the measured output. In the present work, the error corresponds to the speed tracking error between the reference speed and the measured rotor speed,

$$e(t) = \omega_{\text{ref}}(t) - \omega_m(t) \quad (4.22)$$

where $\omega_{\text{ref}}(t)$ is the reference speed and $\omega_m(t)$ is the measured motor speed.

The use of fractional-order integration allows the controller to better represent systems with memory and hereditary effects, thereby improving stability margins and response flexibility. Compared with classical PI controllers, FOPI controllers have been shown to provide:

- improved robustness to parameter variations and external disturbances [77, 78];
- superior steady-state and transient performance due to the additional tuning parameter λ [81, 82];
- enhanced adaptability in applications involving fractional dynamics or requiring fine control precision [83].

Because they do not include a derivative term, FOPI controllers are particularly well suited to systems where derivative action is undesirable, for example, in noise-sensitive applications or systems affected by significant sensor lag.

4.5.3 Tuning Methods for Fractional-Order PI-D Controllers

The tuning of fractional-order PI-D (FOPI-D) controllers involves determining the proportional, integral, and derivative parameters along with the fractional orders that ensure

satisfactory time- and frequency-domain performance. Various analytical, numerical, and rule-based approaches exist in the literature. This subsection summarizes the main categories of tuning techniques and presents the general equations governing each method, while maintaining the referenced foundations.

1. Analytical Methods

Analytical approaches rely on explicit frequency-domain constraints to derive the controller parameters.

- **Phase and Gain Margin Optimization** [81]: This method imposes frequency-domain design specifications directly on the open-loop transfer function. The general tuning conditions are formulated as:

$$|L(j\omega_{gc})| = 1; \quad \angle L(j\omega_{gc}) = -\pi + \phi_m \quad (4.23)$$

where $L(s)$ is the open-loop transfer function and ϕ_m is the desired phase margin. Solving these conditions yields the FOPI-D parameters $(K_p, K_i, K_d, \lambda, \mu)$.

- **Flat Phase Design** [79]: This method enhances robustness by imposing a locally constant phase near the gain-crossover frequency. The flat-phase condition is expressed as:

$$\frac{d}{d\omega} [\angle L(j\omega)]_{\omega=\omega_{gc}} = 0 \quad (4.24)$$

This ensures reduced sensitivity to parameter variations and improved robustness.

- **Internal Model Control (IMC)** [84]: IMC-based tuning relies on approximating the inverse of the plant and applying fractional-order filtering. The general structure of the IMC controller is:

$$C_{\text{IMC}}(s) = P^{-1}(s) F(s) \quad (4.25)$$

where the filter is often a fractional-order form:

$$F(s) = \frac{1}{1 + \lambda s^\alpha} \quad (4.26)$$

2. Numerical Methods

Numerical tuning strategies determine the controller parameters iteratively through optimization or frequency approximation.

- **Optimization-Based Tuning** [82]: A performance index is minimized to tune the controller parameters. The general optimization problem is:

$$\min_{\Theta} J(\Theta) = \int_0^T w(t) |e(t)| dt \quad (4.27)$$

where $\Theta = \{K_p, K_i, K_d, \lambda, \mu\}$ and $w(t)$ is a weighting function (e.g., ITAE). Various numerical solvers—such as Nelder–Mead, PSO, or BCO—can be used.

- **Frequency-Domain Approximation** [83]: Fractional-order operators are implemented using recursive filters. The well-known Oustaloup approximation expresses:

$$s^\alpha \approx K \prod_{k=-N}^N \frac{s + \omega_{z,k}}{s + \omega_{p,k}} \quad (4.28)$$

where α is the fractional order and $(\omega_{z,k}, \omega_{p,k})$ are precomputed break frequencies distributed logarithmically.

3. Rule-Based Methods

These methods generalize classical PID heuristics to fractional-order structures.

- **Ziegler–Nichols Extensions** [84]: Empirical rules are adapted for the FOPI–D controller. A general representation is:

$$K_p = aK_u; \quad K_i = \frac{K_p}{T_i^\lambda}; \quad K_d = K_p T_d^\mu \quad (4.29)$$

where K_u and T_u are the ultimate gain and period, and (a, T_i, T_d) are tuning coefficients defined by the chosen heuristic.

- **F-MIGO Algorithm** [85]: This method tunes the controller by optimizing frequency-domain robustness while balancing sensitivity and tracking. A typical design requirement is:

$$\max_{\omega} |S(j\omega)| \leq M_s \quad (4.30)$$

where $S(j\omega)$ is the sensitivity function and M_s is a robustness bound.

4. Quantitative Feedback Theory (QFT)

QFT-based methods provide robust controller tuning under parametric uncertainty using frequency shaping techniques adapted for fractional-order systems [86]. The general tuning constraint is:

$$|L(j\omega)| \in \mathcal{B}(\omega); \quad \forall \omega \in \Omega \quad (4.31)$$

where $\mathcal{B}(\omega)$ is the set of QFT design bounds ensuring robustness and performance despite model uncertainty.

4.6 Metaheuristic Optimization Algorithms

Metaheuristic optimization algorithms are high-level strategies designed to guide subordinate heuristics to explore the solution space of optimization problems efficiently. Unlike exact methods, metaheuristics are particularly useful for NP-hard problems and those with incomplete, noisy, or complex objective landscapes [87, 88]. These algorithms are nature-inspired computational methods designed to solve complex optimization problems by efficiently exploring large and high-dimensional search spaces. They have gained popularity because of their flexibility, simplicity, and effectiveness in handling non-linear, multi-modal, and non-differentiable problems. Inspired by biological evolution, swarm behavior, and physical phenomena, metaheuristics bypass the limitations of traditional gradient-based methods. Notable examples include the Genetic Algorithms (GA) introduced by Holland [89], the Simulated Annealing (SA) developed by Kirkpatrick et al. [90], the PSO proposed by Kennedy and Eberhart [91], the Ant Colony Optimization (ACO) formulated by Dorigo [92], the Bee Colony Optimization (BCO) introduced by Karaboga [93], the Grey Wolf Optimizer (GWO) proposed by Mirjalili et al. [94], the Firefly Algorithm (FA) developed by Yang [87], the Bat Algorithm (BA) by Yang [95], the Gravitational Search Algorithm (GSA) by Rashedi et al. [96], and the Cuckoo Search (CS) by Yang and Deb [97]. These methods offer significant advantages in terms of robustness and global search capabilities, making them ideal for complex engineering problems such as controller tuning, system identification, and real-time optimization. The ability of these methods to balance exploration and exploitation enables the discovery of near-optimal solutions in challenging problem domains where exact methods are impractical. Figure 4.6 illustrates a general flowchart representing the typical process of a metaheuristic optimization algorithm.

4.6.1 Characteristics of Metaheuristics

Metaheuristic algorithms possess structural properties that distinguish them from classical optimisation techniques. These characteristics enable efficient exploration of complex search spaces while mitigating premature convergence to local optima. A first fundamental feature

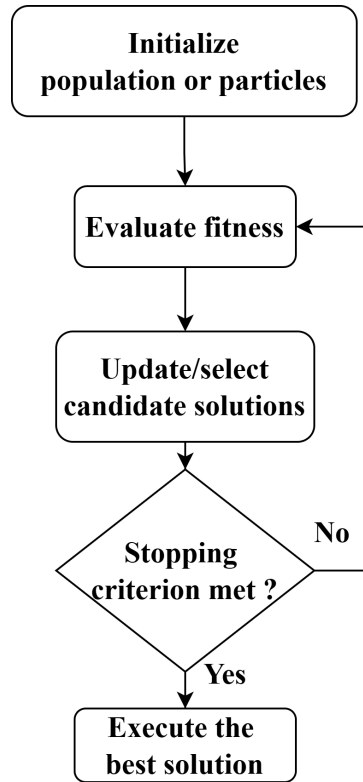


Figure 4.6: General process flowchart of a metaheuristic optimization algorithm.

is the presence of stochastic components: probabilistic elements are used to diversify the search process and avoid being trapped in local minima. This stochasticity allows broader exploration of the solution space than deterministic methods. Typical examples include probabilistic crossover and mutation operators in Genetic Algorithms [98], random coefficients in the velocity update equations of PSO [99], and random differential mutation vectors in Differential Evolution [100].

A second key characteristic is the balance between exploration and exploitation. Exploration refers to the search for new regions in the solution space, whereas exploitation focuses on refining promising candidate solutions. Effective metaheuristics regulate this balance through mechanisms such as temperature schedules in Simulated Annealing [101], hybrid schemes combining global and local search phases [102], or dynamic neighbourhood structures in swarm-based algorithms [103]. An inappropriate balance can lead either to premature convergence (insufficient exploration) or to slow progress (insufficient exploitation).

Metaheuristics are also largely problem-independent. Their design is typically generic, which allows the same optimisation framework to be applied to a wide range of domains with limited problem-specific modifications. They have been successfully employed for combinato-

rial optimisation, for example via Ant Colony Optimisation [104], for continuous optimisation using algorithms such as the Grey Wolf Optimiser [94], and for discrete problems through binary variants of evolutionary or swarm-based methods [105].

Another important property is their gradient-free nature. Metaheuristic algorithms do not require differentiability or convexity of the objective function, which makes them suitable for noisy, discontinuous or black-box problems [106, 107]. This flexibility is particularly advantageous in engineering applications where analytical models are unavailable or incomplete.

From a computational perspective, many metaheuristics are population-based, evolving a set of candidate solutions in parallel, whereas others follow a trajectory-based approach, iteratively modifying a single solution. Population-based algorithms, such as GA, PSO, and BCO, naturally lend themselves to parallel implementations on multicore or GPU architectures [108, 109]. Modern variants further incorporate adaptive mechanisms, for example self-adjusting parameters in Differential Evolution [110] or learning components inspired by reinforcement strategies [111], which improve convergence behaviour under changing conditions.

Finally, metaheuristics include dedicated strategies for constraint handling and scalability. Constraints are typically managed by penalty functions or feasibility-based selection rules [112, 113], whereas high-dimensional problems can be tackled using dimensionality reduction or cooperative coevolutionary schemes [114, 115]. These properties collectively explain the widespread use of metaheuristics in complex optimisation tasks where classical deterministic methods are difficult to apply.

4.6.2 Mathematical Representation

Metaheuristic algorithms can be described mathematically as iterative, stochastic, and adaptive processes. This subsection provides a general formal framework together with representative formulations for widely used algorithms.

1. General iterative metaheuristic framework

A metaheuristic can be abstracted as an iterative process that evolves one or several candidate solutions over time. A generic update rule is

$$x(t+1) = M(x(t), \theta(t), \xi(t), F) \quad (4.32)$$

where $x(t)$ denotes the current solution (or set of solutions) at iteration t , $\theta(t)$ represents adaptive algorithm parameters (e.g., mutation rate, inertia weight), $\xi(t)$ collects stochastic components (random numbers and probabilistic decisions), $M(\cdot)$ is the metaheuristic update operator, and F is the objective function.

This formulation applies to both single-solution (e.g. Simulated Annealing) and population-based (e.g. PSO, GA) algorithms.

2. Population-based metaheuristics

For population-based methods, a set of N candidate solutions $P(t) = \{x_1(t), \dots, x_N(t)\}$ is maintained. The evolution of the population can be written as

$$P(t+1) = M_{\text{pop}}(P(t), \theta(t), \xi(t), F) \quad (4.33)$$

In Genetic Algorithms (GA) [98], for instance, the new population is obtained by applying selection, crossover, and mutation operators:

$$P(t+1) = \text{Selection}(P(t)) + \text{Crossover}(P(t)) + \text{Mutation}(P(t)) \quad (4.34)$$

In Particle Swarm Optimization (PSO) [116], each particle i has a position $x_i(t)$ and a velocity $v_i(t)$, and is guided by its personal best position p_i and the global best position g :

$$v_i(t+1) = w v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t)) \quad (4.35)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (4.36)$$

with w the inertia weight, c_1 and c_2 the learning coefficients, and r_1, r_2 independent random variables.

3. Trajectory-based metaheuristics

Trajectory-based algorithms update a single incumbent solution. In Simulated Annealing (SA) [90], a new candidate x' is generated from $x(t)$ by a random perturbation, and the acceptance rule is

$$x(t+1) = \begin{cases} x', & \text{if } F(x') \leq F(x(t)) \text{ or } \xi < e^{-\Delta F/T} \\ x(t), & \text{otherwise} \end{cases} \quad (4.37)$$

where $\Delta F = F(x') - F(x(t))$, T is the temperature parameter, and ξ is a uniform random number in $(0, 1)$.

4. Stochastic components and probability distributions

The stochastic behaviour of metaheuristics is typically defined via probability distributions. In Evolution Strategies [117], for example, Gaussian mutations are used:

$$x' = x + \sigma \mathcal{N}(0, 1) \quad (4.38)$$

where σ is the mutation step size and $\mathcal{N}(0, 1)$ denotes a standard normal variable.

In Cuckoo Search [97], Lévy flights are employed to generate new solutions:

$$x' = x + \alpha \oplus L(\lambda) \quad (4.39)$$

where α is a scaling factor, $\oplus$ denotes entrywise multiplication, and $L(\lambda)$ is a Lévy-distributed random step.

5. Adaptive parameter control

Many modern metaheuristics dynamically adjust their parameters during the optimisation process. In self-adaptive Differential Evolution [110], for instance, the mutation factor F_i of particle i is updated as:

$$F_i(t+1) = F_{\min} + \xi_1 (F_{\max} - F_{\min}) \quad (4.40)$$

where ξ_1 is a uniform random variable. In Harmony Search [118], the pitch adjustment rate can be varied over iterations:

$$\text{PitchAdjustRate}(t+1) = PAR_{\min} + \frac{t}{T} (PAR_{\max} - PAR_{\min}) \quad (4.41)$$

with T the maximum number of iterations.

6. Constraint handling

Real-world optimisation problems often involve constraints. A common strategy consists of augmenting the objective function with penalty terms [112]:

$$F_{\text{penalty}}(x) = F(x) + \sum_{i=1}^k \lambda_i \max(0, g_i(x))^2 \quad (4.42)$$

where $g_i(x) \leq 0$ are inequality constraints and λ_i are penalty coefficients.

Alternatively, feasibility-based rules can be used [113], in which candidate solutions are compared according to feasibility and objective value:

$$x(t+1) = \begin{cases} x', & \text{if } x' \text{ is feasible, or if } x' \text{ is less infeasible and/or has lower } F(x) \\ x(t), & \text{otherwise} \end{cases} \quad (4.43)$$

7. Convergence considerations

Convergence properties of metaheuristics can be studied via probabilistic models. For Simulated Annealing, a Markov-chain analysis in [119] shows that, under a logarithmic cooling schedule $T(t) \propto 1/\log t$, the probability of reaching a global optimum x^* satisfies:

$$\lim_{t \rightarrow \infty} P(x(t) = x^*) = 1 \quad (4.44)$$

More generally, the so-called no-free-lunch theorem [120] states that no optimisation algorithm, including any metaheuristic, can outperform all others uniformly over the set of all possible objective functions.

4.7 Offline Tuning of Fractional-Order PI Controller via Metaheuristics

Tuning fractional-order (FO) controllers via classical methods is complex and prompts the application of modern optimization techniques to increase stability, robustness, and performance. Metaheuristic techniques, a subset of modern optimizers, have demonstrated efficiency in optimizing FO controllers by employing advanced algorithms that utilize random-search strategies. Examples include Genetic Algorithms (GA) [121], Simulated Annealing (SA) [122], Ant Colony Optimization (ACO) [92], Particle Swarm Optimization (PSO) [91], and Gravitational Swarm Optimizer (GSO) [123]. These methods outperform classical techniques like Gradient Descent (GD) and Least Squares Estimation (LSE) in tuning fractional-order controllers because of the large number of parameters involved. Tuning an FOPID controller is inherently more challenging than tuning a traditional PID controller because it involves five parameters. According to Valerio et al. [124], FOPID tuning methods can be categorized into rule-based, analytical, and numerical methods. Numerical methods, particularly those utilizing evolutionary algorithms, excel in global search capabilities [125]. Various evolutionary algorithms, such as Genetic Algorithms [126], Particle Swarm Optimization [127], Firefly Algorithms [128], Gravitational Search Algorithms (GSA) [129], Prairie Dog Optimization (PDO) algorithm [130], and Mountain Gazelle Optimization (MGO) [131], have been employed for FOPID tuning.

The use of a fractional-order PI controller (FOPI) has gained significant interest among researchers employing Metaheuristic Algorithms (MHAs) in optimization and control systems. In 2015 Maamir et al. [132] used PSO to tune FOPI controllers for thermal devices in virtual reality, resulting in effective control. Additionally, in 2015, Agarwal et al. [133] optimized

FOPI controllers for DC motor speed control via PSO, and achieved better performance with real-time tuning in LabVIEW™. In 2018, Leena et al. [134] used Social-Group-Optimisation (SGO) to design FOPI/PID controllers, which improved the performance and stability of various systems. In 2019, Zamee and Won [135] proposed a Plant Propagation Algorithm (PPA) based FOPI controller for controlling grid-connected PV systems. In 2020, Guha et al. [136] designed an FOPI-D controller to manage load perturbations and damp system oscillations. Additionally, in 2020, Sahul Hameed and Ramasubramanian [137] reported that an FOPI controller optimized by Moth Flame Optimization (MFO) improved the steady-state and dynamic performance. In 2021, Kakkar et al. [138] demonstrated that an FOPI controller enhances the robustness of PWM rectifier control. In 2022, Barakat [139] introduced a chaos game optimization tuned FOPI controller for load frequency control, which yielded promising results. In 2022, Ramadan et al. [140] proposed a meta-heuristic-based Near Optimal Algorithm (NOA) FOPI controller to enhance on-grid fuel cell performance. In 2022, Bouderrès et al. [141] reported that the PSO-FOPI controller outperforms the classical PI controller in terms of rapidity, stability, and precision. In 2022, Çelebi and Başçi [142] developed an improved PSO-based FOPI controller for grid formation in a bidirectional three-phase DC-AC power inverter, significantly reducing the computation time. In 2023, Altawil et al. [143] used fractional order PI controllers to regulate the active and reactive power of solar inverters, compensating for over-voltage and under-voltage. In 2023, Labed et al. [144] proposed the use of FOPI controllers, optimized with PSO and ANFIS for fault detection to improve wind turbine control and stability. In 2023, Özyetkin and Birdane [145] focused on control strategies for systems with FO delays and proposed a PI controller optimized with PSO to increase system performance. Additionally, in 2023, Dwivedi et al. [146] integrated voltage-oriented PWM control with a FOPI controller for a three-phase electric vehicle charger, optimizing parameters with the Water Cycle Algorithm (WCA) for enhanced performance flexibility.

4.7.1 Problem Formulation and Objective Function

The optimization of the FOPI is a crucial task that requires efficient search methods to determine the optimal controller parameters. Metaheuristic algorithms have proven to be effective in handling such optimization problems by providing near-optimal solutions without requiring gradient information. In this study, three widely used metaheuristic algorithms are considered for offline optimization:

- **Particle Swarm Optimization (PSO):** Inspired by the social behavior of bird flocks and fish schools, PSO optimizes a problem by iteratively updating the position and

velocity of particles in the search space [147].

- **Bee Colony Optimization (BCO):** On the basis of the foraging behavior of bees, BCO divides the search agents into employed and onlooker bees to explore and exploit the search space efficiently [148].
- **Grey Wolf Optimizer (GWO):** Inspired by the hunting strategy of grey wolves, GWO mimics the leadership hierarchy and cooperative hunting mechanism to find the best solution [149].

To achieve optimal performance, the controller parameters are tuned via an objective function that evaluates system behavior on the basis of specific performance criteria. Optimization algorithms such as PSO, BCO, and GWO are employed to iteratively adjust these parameters, ensuring improved transient and steady-state performance.

- **Integral Absolute Error (IAE):** Emphasizes minimizing the overall error magnitude.
- **Integral of Time-Weighted Absolute Error (ITAE):** This method assigns higher weights to later errors, improving the system settling time.

These indices are mathematically defined as follows:

$$IAE = \int_0^{tsim} |e(t)| dt \quad (4.45)$$

$$ITAE = \int_0^{tsim} t|e(t)| dt \quad (4.46)$$

In this study, the ITAE criterion is selected as the objective function, as it effectively reduces overshoot and settling time.

4.7.2 Design Steps of Offline FOPI Optimization

The steps and mathematical formulation of these algorithms are summarized in Table 4.2. The following steps summarize the procedure. The objective is to determine the optimal parameters of the FOPI controller, represented as a vector in the solution space:

$$X = \{X_1, X_2, X_3\} = \{K_p, K_i, \lambda\} \quad (4.47)$$

where $X_1 = K_p$ is the proportional gain, $X_2 = K_i$ is the integral gain, and $X_3 = \lambda$ is the fractional order of integration. The cost function is formulated on the basis of control performance criteria, as defined in Equation 4.46.

Table 4.2: Stepwise explanation and mathematical formulation of PSO, BCO, and GWO.

Algorithm Steps	Mathematical Formulation
Step 1: Initialization	
Initialize population/swarm within the search space.	$\mathbf{x}_i^0 = \mathbf{x}_{\min} + r(\mathbf{x}_{\max} - \mathbf{x}_{\min}) \quad (4.48)$
Step 2: Evaluate Fitness Function	
Compute the objective function for each solution.	$ITAE = \int_0^{T_s} t e(t) dt \quad (4.49)$
Step 3: Update Positions	
PSO: Update velocity and position.	$\mathbf{v}_i^{t+1} = w\mathbf{v}_i^t + c_1r_1(\mathbf{p}_i - \mathbf{x}_i^t) + c_2r_2(\mathbf{g} - \mathbf{x}_i^t) \quad (4.50)$
	$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_i^{t+1} \quad (4.51)$
BCO: Employed bees update food sources.	$\mathbf{x}_{i,\text{new}} = \mathbf{x}_i + \phi(\mathbf{x}_i - \mathbf{x}_{\text{neighbor}}) \quad (4.52)$
GWO: Wolves update positions relative to leaders.	$\mathbf{x}_i^{t+1} = \frac{\mathbf{x}_\alpha + \mathbf{x}_\beta + \mathbf{x}_\delta}{3} \quad (4.53)$
Step 4: Selection and Information Sharing	
PSO: Update personal and global best.	$\mathbf{p}_i = \arg \min J(\mathbf{x}_i), \quad \mathbf{g} = \arg \min J(\mathbf{p}_i) \quad (4.54)$
BCO: Onlooker bees select food sources.	$P_i = \frac{J_{\text{best}} - J_i}{\sum (J_{\text{best}} - J_j)} \quad (4.55)$
GWO: Adaptive coefficients adjust movement.	$A = 2a \cdot r - a, \quad C = 2r \quad (4.56)$
Step 5: Exploration and Exploitation	
PSO: Adjust inertia weight dynamically.	$w = w_{\max} - \frac{t(w_{\max} - w_{\min})}{T} \quad (4.57)$
BCO: Scout bees replace abandoned food sources.	$\mathbf{x}_i^{\text{new}} = \mathbf{x}_{\min} + r(\mathbf{x}_{\max} - \mathbf{x}_{\min}) \quad (4.58)$
GWO: Wolves dynamically adjust their movement.	$\mathbf{x}_i^{t+1} = \mathbf{x}_p - A \cdot \mathbf{C} \cdot \mathbf{x}_p - \mathbf{x}_i \quad (4.59)$
Step 6: Stopping Criteria	
Stop when convergence or max iterations is reached.	Stop if $\min J(\mathbf{x}_i) < \epsilon$ or $t = T_{\max}$ (4.60)

4.8 Hybrid Fuzzy-PSO FOPI Controller Design for EV Motors

Recent advancements have introduced hybrid approaches that integrate fuzzy logic with meta-heuristic algorithms to increase the adaptability of FOPI controllers. Several studies have demonstrated the effectiveness of these strategies, specifically in combining FOPI with fuzzy logic and metaheuristics. Notable contributions include the works of Mohammad Ali Labbaf-Khaniki et al. [150], Sekyere et al. [151], as well as [152], [153], [154], [155], [156], and [157]. These hybrid controllers dynamically adjust parameters based on real-time system feedback, significantly improving disturbance rejection and adaptability under varying operating conditions. Despite these advancements, further research is needed to enhance the real-time performance and robustness of FOPI controllers, particularly for critical applications. However, challenges persist in achieving real-time adaptability and robustness for critical applications like BLDC motor control in electric vehicles (EVs). To address these gaps, this work introduces a Hybrid Fuzzy-PSO self-tuning FOPI controller, uniquely designed for high-precision speed regulation in EV traction systems.

4.8.1 Hybrid Control Architecture and Adaptation Workflow

The proposed hybrid control architecture is designed to achieve real-time adaptability and high-performance speed regulation for electric vehicle traction systems. As shown in Figure 4.7, the controller combines two complementary adaptive mechanisms, each targeting a distinct aspect of the FOPI control structure. This separation allows the controller to address both parametric uncertainty and dynamic operating variations in a coordinated manner.

- **PSO-Based Parameter Optimization:** A PSO algorithm is implemented online to adjust the proportional and integral gains, K_p and K_i , at each sampling instant. Unlike classical offline metaheuristic tuning approaches, the PSO operates in real time and adapts the gains according to the instantaneous speed error $e(t)$ and its variation $\Delta e(t)$. The optimization process minimizes a time-domain performance criterion based on the integral of ITAE, while the gain update rules are governed by the iterative expressions given in Equations 4.62 and 4.63. This mechanism ensures fast convergence and improved robustness under varying load and speed conditions.
- **Fuzzy Logic-Based Fractional-Order Adjustment:** In parallel with gain optimization, a Mamdani-type fuzzy inference system is employed to regulate the fractional order λ of the integrator. The fuzzy controller processes the normalized speed

error and its rate of change as inputs, and generates an adaptive value of λ through centroid-based defuzzification, according to the rule base defined in Table 4.3. By dynamically shaping the fractional-order dynamics, this mechanism enhances transient behavior and mitigates overshoot and oscillations during load disturbances and rapid operating transitions.

4.8.2 Adaptive Mechanisms of the Hybrid Fuzzy–PSO FOPI Controller

This subsection details the adaptive mechanisms that govern the operation of the hybrid Fuzzy–PSO FOPI controller and explains how these mechanisms contribute to improved performance in electric vehicle traction applications. The proposed strategy is specifically designed to handle the nonlinear, time-varying, and disturbance-prone nature of BLDC motor drives.

- **Dual Adaptation Structure:** Unlike existing hybrid control approaches such as [155], which often rely on partially adaptive or fixed hybrid configurations, the proposed controller explicitly decouples the adaptation of the controller gains K_p and K_i from the adjustment of the fractional order λ . The PSO algorithm is dedicated to optimizing the gain parameters, while fuzzy logic governs the fractional dynamics. This separation enables independent and targeted optimization of transient response and steady-state accuracy.
- **Bounded Real-Time PSO Optimization:** To ensure stable online operation, the PSO search space is constrained by predefined bounds on the adaptive parameters δ_1 and δ_2 . These bounds are selected based on empirical analysis and system stability considerations, preventing divergence and excessive parameter oscillations. As a result, the controller remains stable and effective even under highly dynamic driving conditions, such as those encountered in standardized cycles like the NEDC.
- **EV-Oriented Fuzzy Rule Design:** The fuzzy rule base is constructed to reflect the specific dynamic requirements of electric vehicle traction systems. As summarized in Table 4.3, the rules enforce rapid reduction of the fractional order λ during aggressive acceleration phases characterized by large values of e and Δe , while promoting smoother adjustments during steady-state operation. This behavior aligns the controller dynamics with motor torque demand variations and contributes to enhanced ride comfort and efficiency.

4.9 Design Steps of the Proposed Hybrid Self-Tuning Fuzzy-PSO FOPI Controller

This section presents a novel parameter-tuning approach for an FOPI controller with predefined motor parameters. As depicted in Figure 4.7, the proposed tuning scheme combines two controllers to achieve the desired control law. The speed error serves as an input to an adaptive algorithm based on PSO, which tunes the proportional K_p and integral K_i gains at each sampling time step. Additionally, the speed error and its variation are used as inputs to a fuzzy logic controller, which adjusts the integrator parameter λ . The Mamdani inference system, with its fuzzification and defuzzification processes, is employed to modify λ based on expert-defined rules [158]. This ensures smooth and adaptive parameter tuning, improving system performance under varying conditions.

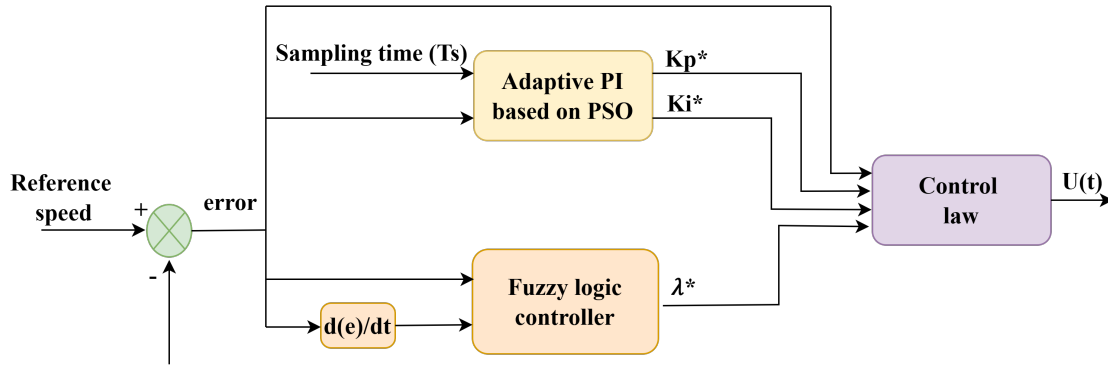


Figure 4.7: Diagram of the hybrid fuzzy-PSO self-tuning fractional order PI controller.

4.9.1 Fuzzification, Inference, and Defuzzification for Adjusting λ

The fuzzy logic controller adjusts the integrator parameter λ by processing the speed error and its variation through fuzzification, inference, and defuzzification steps.

1. Fuzzification

The first step in the fuzzy logic process is fuzzification, where crisp input values (speed error e and error variation de) are mapped to fuzzy values. This is done via predefined membership functions, as illustrated in Figure 4.8.

- **Speed Error (e):** The speed error is categorized into linguistic terms such as *Negative Large (NL)*, *Negative Medium (NM)*, *Negative Small (NS)*, *Zero (Z)*, *Positive Small (PS)*, *Positive Medium (PM)*, and *Positive Large (PL)*, on the basis of the membership functions shown in Figure 4.8(a).

- **Error Variation (de):** Similar to the speed error, the error variation is fuzzified into the same linguistic terms, as shown in Figure 4.8(b).

Each input value is then associated with a degree of membership in the corresponding fuzzy set, providing a fuzzy representation of the inputs.

2. Inference

Once the inputs are fuzzified, the next step is inference. The Mamdani inference system applies fuzzy rules to the fuzzified inputs to generate a fuzzy output. The fuzzy rule base is defined in Table 4.3, where each rule specifies the output λ based on combinations of the speed error e and its variation de .

- **Rule Evaluation:** Each rule is evaluated in term of the degree of membership of the fuzzified inputs e and de in the corresponding fuzzy sets.
- **Example Rule:** For illustrating, if the speed error e is *Negative Large (NL)* and the error variation de is also *Negative Large (NL)*, the output λ is determined to be *Positive Large (PL)*. Similarly, if $e = Z$ and $de = PS$, then λ will be *Zero (Z)*.
- **Rule Aggregation:** The individual fuzzy outputs from all rules are aggregated to form a single fuzzy output set. This is done via fuzzy union operations, which consider the degree of membership for each rule's output.

3. Defuzzification

Finally, the fuzzy output is converted into a crisp value that can be used to adjust the controller's parameters. In this system, the Center of Gravity (COG) method is used for defuzzification, which calculates the weighted average of the fuzzy output sets. The crisp value for λ is obtained as follows:

$$\lambda = \frac{\sum (\mu(\lambda_i) \cdot \lambda_i)}{\sum \mu(\lambda_i)} \quad (4.61)$$

where:

- $\mu(\lambda_i)$: The membership value of each output fuzzy set λ_i ,
- λ_i : The crisp value corresponding to the output fuzzy set,
- **The sum:** Taken over all possible output values.

This process results in a precise, real-valued output for λ , which is then used to update the controller parameters in real time. The entire fuzzy logic process ensures that the integrator parameter λ is dynamically adjusted based on the system's performance, improving control system efficiency and adaptability.

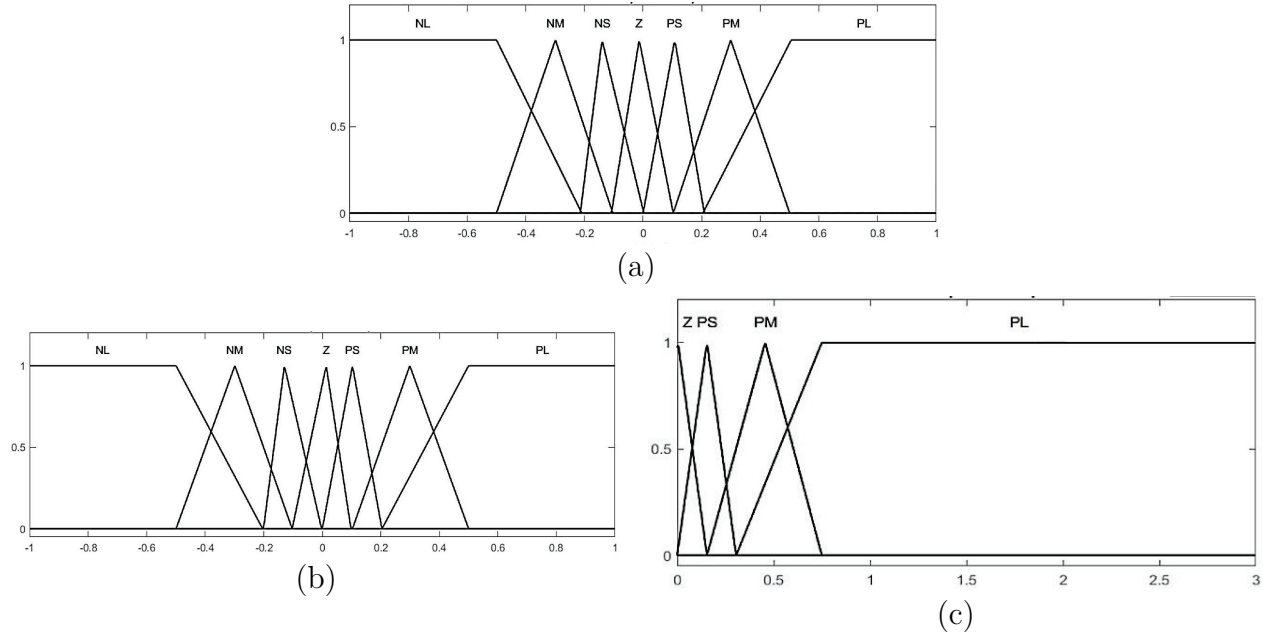


Figure 4.8: Fuzzy membership functions (a) for Input Error, (b) Input Error variation (de), and (c) Output Lambda λ .

Table 4.3: Rule base for the fuzzy logic controller.

$\Delta e / e$	NL	NM	NS	Z	PS	PM	PL
NL	PL	PL	PL	PL	PL	PL	PL
NM	PL	PL	PM	PM	PM	PL	PL
NS	PM	PM	PS	PS	PS	PM	PM
Z	PS	PS	Z	Z	Z	PS	PS
PS	PM	PM	PS	PS	PS	PM	PM
PM	PL	PL	PM	PM	PM	PL	PL

4.9.2 Adaptive Fractional-Order PI Controller Design with PSO

In control theory, designing an adaptive fractional-order PI (FOPI) controller involves defining update laws for the proportional and integral gains, K_p and K_i , to ensure stability and optimal performance. The equations governing these updates are derived based on fundamental principles of feedback control, optimization, and fractional calculus. The stability of the closed-loop system under the proposed A-HFOPI controller is ensured both theoretically

and practically. From a theoretical perspective, the FOPI structure provides better phase characteristics and improved robustness compared to traditional PI controllers, as supported in prior works such as in [77]. The controller maintains bounded output for any bounded input, fulfilling the condition of BIBO (Bounded-Input Bounded-Output) stability. This ensures that the system will not show divergent responses under normal operating conditions, even with real-time parameter adaptation.

4.9.3 Adaptive Parameter Adjustment Using Error Dynamics

To ensure stability and optimal performance, the proportional and integral gains of the controller, K_p and K_i , are adaptively adjusted base on real-time error dynamics. These gains are defined as follows:

- The proportional gain K_p is governed by the inverse of $\alpha(k)$, ensuring that any variation in $\alpha(k)$ directly affects the control action.
- The integral gain K_i is determined as the ratio $\beta(k)/\alpha(k)$, allowing for an adaptive integral action.

To dynamically adjust these parameters, the update laws for $\alpha(k)$ and $\beta(k)$ are formulated in terms of the error signal $e(k)$, its history, and its integral. The key objective is to modify the controller parameters in real time for improved system performance. The adaptation mechanism is as follows:

$$\alpha(k) = \alpha(k-1) - \delta_1 e(k)e(k-1)T_s \quad (4.62)$$

$$\beta(k) = \beta(k-1) + \delta_2 \int e(k-1)T_s \quad (4.63)$$

These equations define how the controller updates its parameters at each time step k to adapt to varying system conditions.

The formulation of these update laws is based on gradient-based adaptation and heuristic optimization techniques:

- *Error-Weighted Update for $\alpha(k)$* : The term $e(k)e(k-1)T_s$ represents a learning rule where the change in $\alpha(k)$ is proportional to the product of the current and previous errors. This ensures that if the error persists over multiple time steps, the adaptation effect is reinforced.

- *Integral-Based Update for $\beta(k)$* : The integral of the past error influences $\beta(k)$, ensuring that the accumulated error dynamically adjusts the integral term, enhancing robustness against disturbances.

These update rules are designed to align with Lyapunov stability principles, ensuring that the system remains stable as parameters evolve.

4.9.4 Particle Swarm Optimization for Online Parameter Tuning Approach

To determine the optimal values of δ_1 and δ_2 , PSO is utilized, and the algorithm orchestrates the optimization process by iteratively updating candidate solutions based on individual and global best positions, refining the update coefficients to achieve the best closed-loop performance. Additionally, a mechanism confines α and β within predefined bounds, enhancing stability. The accumulation of integral error over time enables precise control adjustments. The final expressions for the proportional and integral gains are derived as:

$$K_p = \frac{1}{\alpha(k)} \quad (4.64)$$

$$K_i = \frac{\beta(k)}{\alpha(k)} \quad (4.65)$$

This formulation ensures that K_p and K_i dynamically evolve to optimize control precision and stability. Table 4.4 shows the PSO algorithm process of the proposed tuning method [158].

The PSO algorithm continuously tunes K_p and K_i on the basis of current speed error and its evolution, enabling the controller to adapt to variations in load and operating conditions. The fractional order λ is adjusted via a fuzzy logic controller, which takes the speed error and its rate of change as inputs. Based on predefined rules and membership functions, the fuzzy controller dynamically modifies λ to fine-tune the system's response to changing conditions.

The adjusted values of K_p , K_i , and λ are then used to compute the control signal applied to the BLDC motor, aiming to minimize the speed error. The adaptive FOPI controller continuously monitors the motor's performance and dynamically updates its parameters in real time. This ensures optimal performance and robustness, even in the presence of disturbances or system dynamics variations. By integrating adaptive tuning mechanisms, the system achieves precise and efficient speed control, ensuring smooth operation and quick response to changing conditions.

Table 4.4: Step-by-step PSO optimization process for adaptive K_p and K_i .

Step	Procedure
1. Initialize PSO	Define PSO parameters: number of particles, initial velocities, and limits for coefficients δ_1, δ_2 . Generate an initial population of particles (α, β, γ) randomly (Equations 4.62 and 4.63) .
2. Read real-time signals	Acquire data from the BLDC motor (speed error $e(t)$ Equation 4.22) and Compute the derivative of the error $\dot{e}(t)$.
3. Compute K_p and K_i using the learning rule	Extract δ_1, δ_2 from a PSO particle. Update K_p and K_i based on the adaptive rule (Equations 4.64 and 4.65).
4. Apply K_p and K_i to the controller	Update parameters in the real-time controller (dSPACE / Simulink). Then, allow the motor to run with the new gains.
5. Evaluate performance (ITAE)	Measure the motor's response over a given time horizon. Compute the ITAE integral (Equation 4.46).
6. Update best solutions (pBest, gBest)	Compare the obtained ITAE with previous particle values. Update **pBest** (best personal solution of the particle) and Update **gBest** (best global solution found) (Equation 4.54).
7. Update PSO particles	Compute new particle velocities using the PSO equation. Update particle positions (δ_1, δ_2) .
8. Check stopping criteria	Verify if the maximum number of iterations is reached **or** if ITAE is sufficiently low. **If yes** , proceed to Step 9. **If not** , go back to Step 2 for the next iteration.
9. Apply optimized parameters	Once the best δ_1, δ_2 are found, fix them for the adaptive system, and continue motor operation with these values.
10. End process	Optimization is complete, and the system now operates with the best K_p, K_i .

4.10 Conclusion

This chapter has presented a comprehensive framework for energy and motor control in hybrid electric vehicles. On the supply side, an energy management system based on frequency separation and Lyapunov control was developed to allocate power dynamically between the lithium-ion battery and the supercapacitor while preserving DC bus voltage stability. On the traction side, the BLDC drive was equipped with a fractional-order PI (FOPI) speed controller and an adaptive flux control scheme for loss minimization.

The fundamentals of fractional-order control theory and the advantages of FOPI controllers over classical PI/PID structures were reviewed, together with analytical, rule-based, and numerical tuning approaches. Offline optimization of the FOPI parameters was performed

using metaheuristic algorithms such as PSO, BCO, and GWO, with objective functions based on IAE and ITAE indices.

To improve real-time behaviour, a hybrid Fuzzy–PSO self-tuning FOPI controller was introduced. In this configuration, fuzzy logic adjusts the fractional order, and PSO adapts the proportional and integral gains, providing enhanced speed tracking, reduced torque ripple, and improved energy efficiency under varying driving conditions.

Chapter 5 reports the simulation, hardware-in-the-loop (HIL), and real-time experimental results that assess the performance and practicality of the control and energy management strategies developed in the present chapter.

Chapter 5

Experimental Validation and Performance Analysis

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5.1 Introduction

This chapter presents the experimental validation and performance analysis of the proposed energy management and motor control strategies developed throughout this thesis. The aim is to assess the real-time behavior, robustness, and effectiveness of the proposed methods under realistic operating conditions. To this end, both Hardware-in-the-Loop (HIL) simulation and real-time experimental tests are carried out using dedicated test benches.

The chapter is structured to provide a detailed description of the experimental platforms, followed by a comprehensive evaluation of the energy management system on the power source side and the control system on the traction side. Results obtained from simulation, HIL, and real-time implementation are compared and discussed to demonstrate the performance gains achieved through the proposed approaches.

A comparative analysis is also conducted to benchmark the developed strategies against some other techniques, highlighting improvements in terms of response time, energy efficiency, system stability, and adaptability to dynamic conditions. The findings provide strong evidence of the feasibility and superiority of the integrated control system in practical electric vehicle applications.

5.2 Description of the Experimental Test Benches

To validate the proposed control and energy management strategies under realistic conditions, two complementary experimental platforms were developed and utilized: a Hardware-in-the-Loop (HIL) simulation setup and a real-time laboratory test bench. All real-time experimental tests were carried out at the LGEB Laboratory (Laboratoire de Génie Électrique de Biskra), University of Biskra, Algeria. These platforms were designed to emulate the dynamic behavior of an electric vehicle powertrain and to provide a reliable environment for testing control algorithms under various operating scenarios.

The HIL setup allows for rapid prototyping and validation by interfacing real-time digital controllers with simulated plant models, ensuring closed-loop operation without the risks associated with full physical testing. It provides a safe and flexible framework for assessing the performance of the proposed control strategies under varying load, speed, and fault conditions.

In contrast, the real test bench setup involves actual hardware components, including a BLDC motor, power converters, and data acquisition systems. This setup enables thorough evaluation of the control system performance in practical scenarios, including sensor

noise, thermal effects, and physical limitations of components. Together, these experimental benches provide a comprehensive validation environment for assessing the effectiveness, robustness, and real-time feasibility of the developed energy management and motor control strategies.

5.2.1 Description of Hardware-in-the-Loop (HIL) Setup

The Hardware-in-the-Loop (HIL) platform provides a real-time validation framework for the proposed control strategy of the traction system. It allows closed-loop testing between the controller and a simulated model of the electric vehicle powertrain, enabling realistic system evaluation without the risks and costs of full-scale physical experimentation.

A simplified block diagram of the internal architecture of the DS1104/CLP1104 controller board, highlighting the master processor, slave DSP, memory, and input-output subsystems, is presented in Figure 5.1.

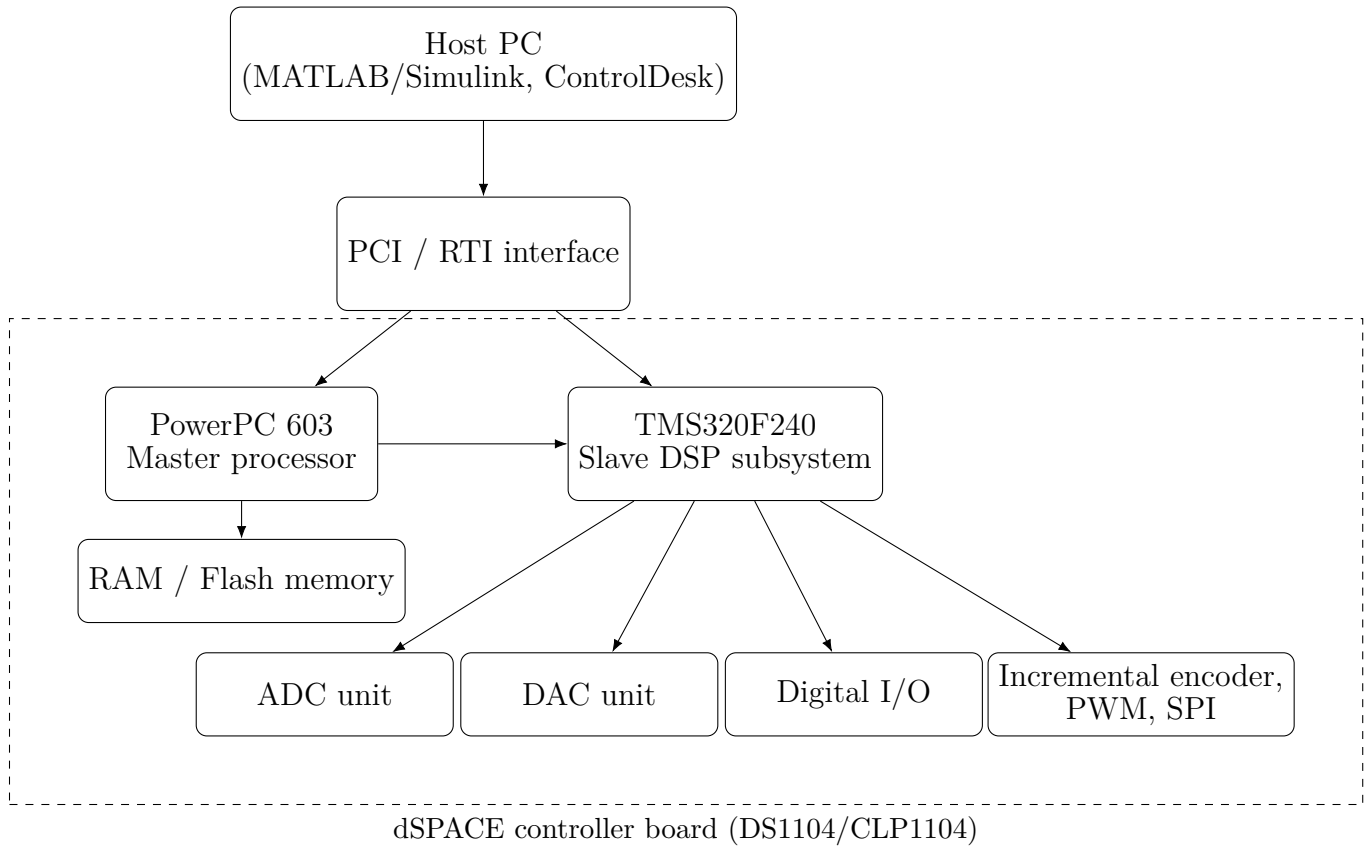


Figure 5.1: Simplified internal architecture of the dSPACE controller board.

The setup is based on two dSPACE CLP1104 units, each functioning as an independent real-time processing module. The dSPACE CLP1104 system integrates an embedded digital

signal processor (DSP) and multiple analog/digital input-output (I/O) channels, enabling high-speed data acquisition and PWM generation. Its ControlDesk interface, combined with MATLAB/Simulink, provides an environment for algorithm implementation, monitoring, and signal exchange. This configuration facilitates the simultaneous execution of control and plant models in real time, ensuring deterministic timing and accurate emulation of the BLDC motor drive system. The front connector panel of the dSPACE CLP1104, which provides access to the ADC, DAC, digital I/O, and incremental encoder interfaces used in this work, is shown in Figure 5.2.



Figure 5.2: Connector panel of the dSPACE CLP1104 used for experiments.

In the proposed setup, the two dSPACE boards are connected in a master-slave configuration. Monitor 1 and the first dSPACE CLP1104 (#1) execute the control circuit simulation (control system), whereas Monitor 2 and the second dSPACE CLP1104 (#2) execute the plant simulation (power system). Communication between the two units is established through analog and digital I/O channels, forming a complete closed-loop interaction that reproduces the dynamic behaviour of the traction system. The main signal paths between the master and slave dSPACE CLP1104 units, including ADC and DAC channels, PWM commands, and digital I/O links, are summarised in the schematic diagram of Figure 5.3.

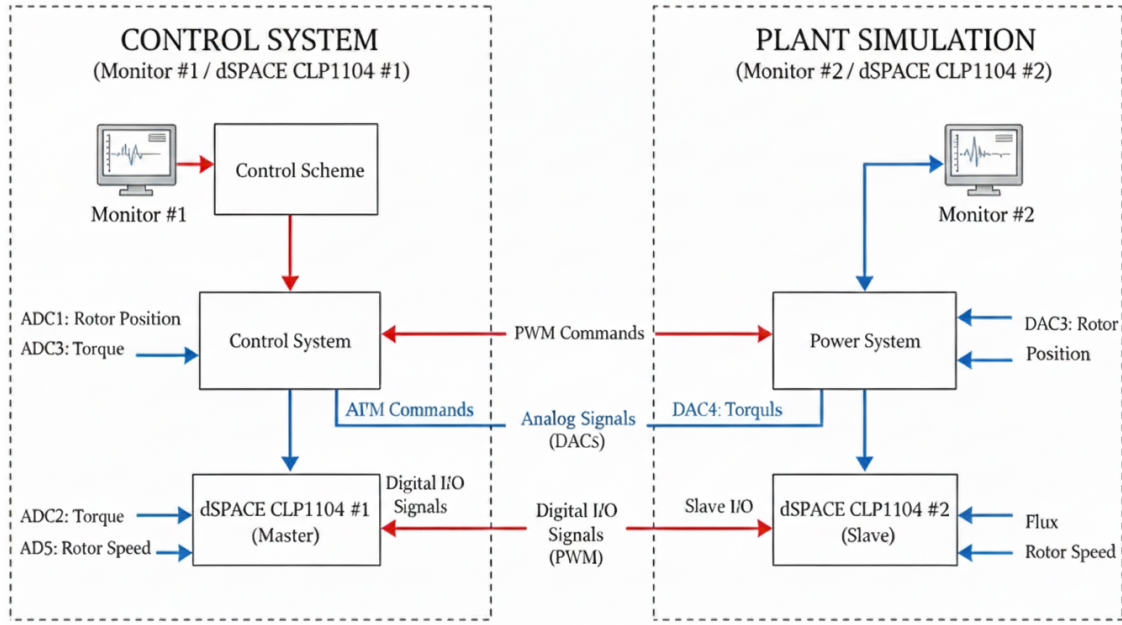


Figure 5.3: Schematic representation of the Hardware-in-the-Loop setup and signal exchange between the two dSPACE CLP1104 units.

On the controller side (Monitor 1), key feedback signals from the simulated plant are received through analog input channels:

- ADC1 reads the rotor position.
- ADC2 captures the torque signal.
- ADC3 receives the flux signal.
- ADC5 monitors the rotor speed.

The controller processes these feedback variables to generate PWM control signals that are transmitted via the Slave I/O interface to drive the inverter gates of the simulated plant.

On the plant side (Monitor 2), the inverter gate signals are received via the I/O interface, and the plant model generates the corresponding analog outputs representing the system response. These are transmitted back to the controller through the following DAC channels:

- DAC3 carries the rotor position signal.
- DAC4 transmits the torque signal.
- DAC6 represents the flux signal.
- DAC8 outputs the rotor speed.

This continuous bidirectional signal exchange emulates the physical dynamics of the BLDC motor drive system under real-time constraints, allowing the evaluation of controller performance in terms of speed tracking, disturbance rejection, and stability. The complete Hardware-in-the-Loop experimental configuration used for validating the traction system control strategy is illustrated in Figure 5.4, which shows the two dSPACE CLP1104 units, their associated monitors, and the real-time signal interfacing between the control and plant subsystems.

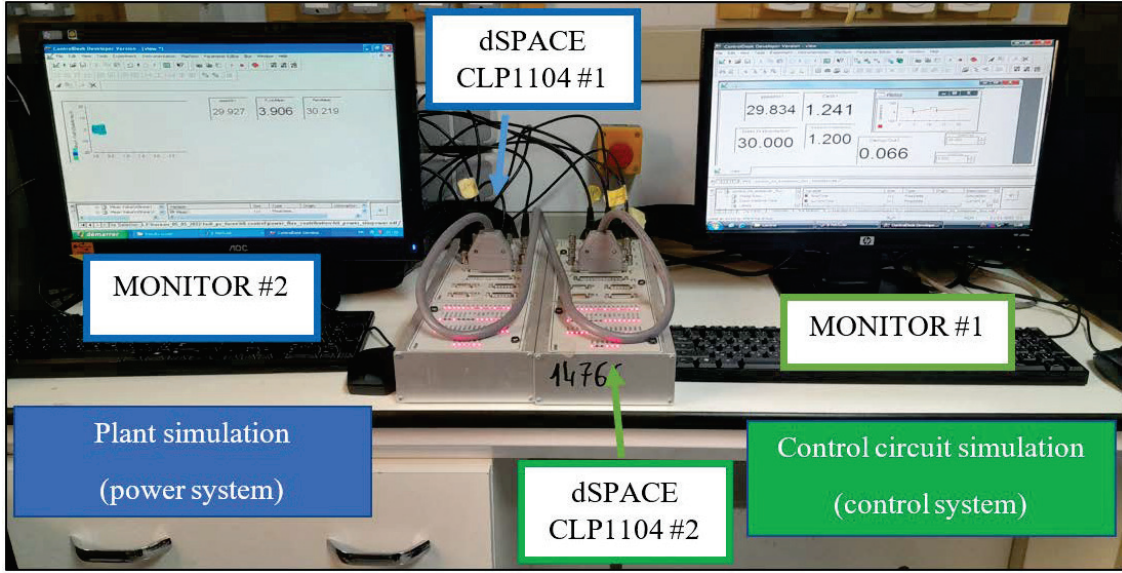


Figure 5.4: Hardware-in-the-Loop setup for the traction system validation.

5.2.2 Description of the Real Test Bench Setup

The real-time experimental validation of the proposed control strategy was carried out using a laboratory-scale test bench designed to replicate the main components of an electric vehicle (EV) traction system. The setup consists of a BLDC motor mechanically coupled to a DC motor acting as a load, where the latter is connected to a resistive charge that provides the braking torque. The drive is supplied by a SEMIKRON-based inverter, and the overall system is supervised by a dSPACE CLP1104 platform for real-time implementation and data acquisition. In this configuration, the traction subsystem is powered from a regulated DC link dedicated solely to the motor drive. A global schematic of the real-time traction test bench, showing the power supply stages, SEMIKRON inverter, BLDC motor, load motor, resistive load bank, measurement sensors, and dSPACE CLP1104 controller with the monitoring PC, is provided in Figure 5.5.

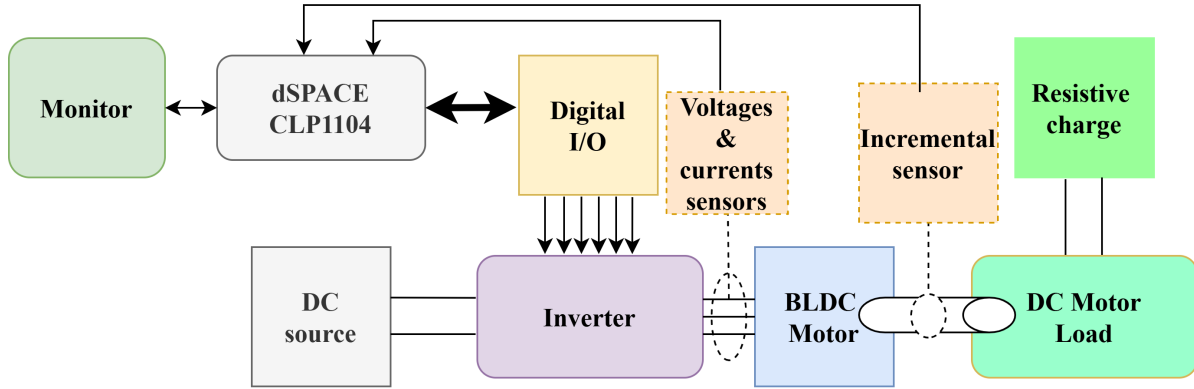


Figure 5.5: Schematic diagram of the real-time BLDC traction test bench.

The dSPACE CLP1104 controller, similar in architecture to the DS1104, integrates a high-performance real-time processor and a DSP coprocessor for rapid control computations. It is equipped with multiple analog-to-digital converters (ADCs), digital-to-analog converters (DACs), digital I/O lines, and PWM outputs, enabling direct interfacing with the SEMIKRON inverter and the measurement sensors. Incremental encoder inputs are used to read the rotor position and speed of the BLDC motor, ensuring accurate feedback for closed-loop control. The Real-Time Interface (RTI) and ControlDesk software facilitate graphical interaction, online parameter adjustment, and continuous monitoring during experiments.

The inverter section is based on SEMIKRON SKHI22 driver cards interfaced with SKM50GB123 IGBT power modules. The main components of the inverter assembly are shown in Figure 5.6. In Figure 5.6(a), the three inverter legs and their power supply connections are visible, providing the three-phase excitation required by the BLDC motor. Figure 5.6(b) highlights the driver board where the gate signals coming from the dSPACE CLP1104 are transmitted to the IGBT modules through the SKHI22 interfaces. Figure 5.6(c) illustrates one of the DC-bus capacitors; two such capacitors are mounted in the inverter to stabilise the DC-link voltage and to filter high-frequency switching ripple. An auxiliary interface board adapts the dSPACE output signals (0/5 V TTL logic) to the 0/15 V logic levels required by the IGBT drivers via a buffering stage based on 74LS00 NAND gates followed by a voltage step-up circuit using 74LS17 open-collector inverters.

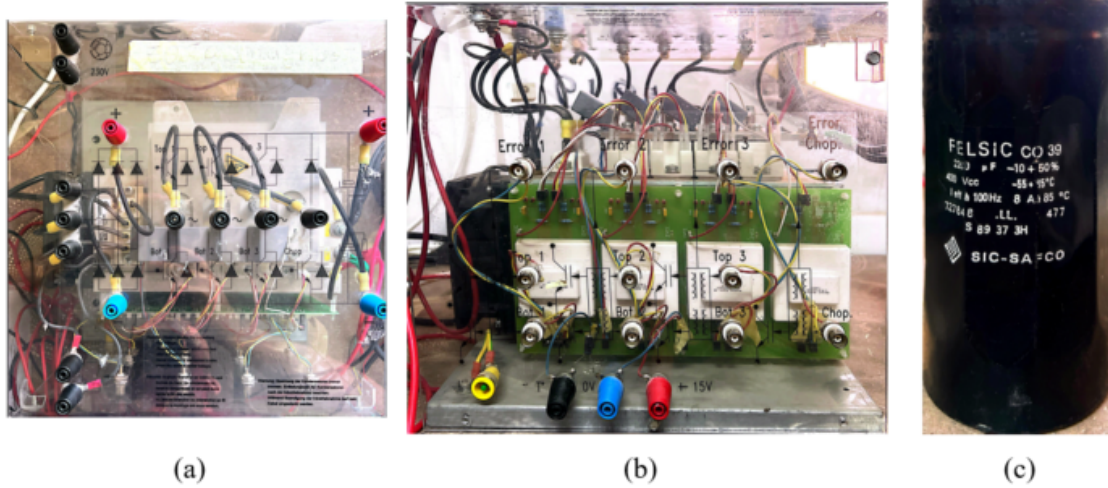


Figure 5.6: Inverter hardware used in the traction test bench: (a) inverter legs and DC power supply connections; (b) driver board transmitting gate signals to the IGBT modules and (c) DC-bus capacitor used for DC-link voltage stabilisation.

The measurement system integrates LEM LA25-NP current sensors and LEM LV25P voltage sensors, both operating on the Hall-effect principle, together with an incremental sensor for speed measurement. These devices provide galvanic isolation, high accuracy, and a broad dynamic range suitable for dynamic traction tests. Each measurement channel incorporates an anti-aliasing filter to reduce noise and to ensure accurate signal conditioning before being processed by the dSPACE ADC inputs. The three main sensors employed in the experimental setup are presented in Figure 5.7, where (a) shows the current sensor, (b) the voltage sensor, and (c) the incremental sensor used to acquire rotor speed.

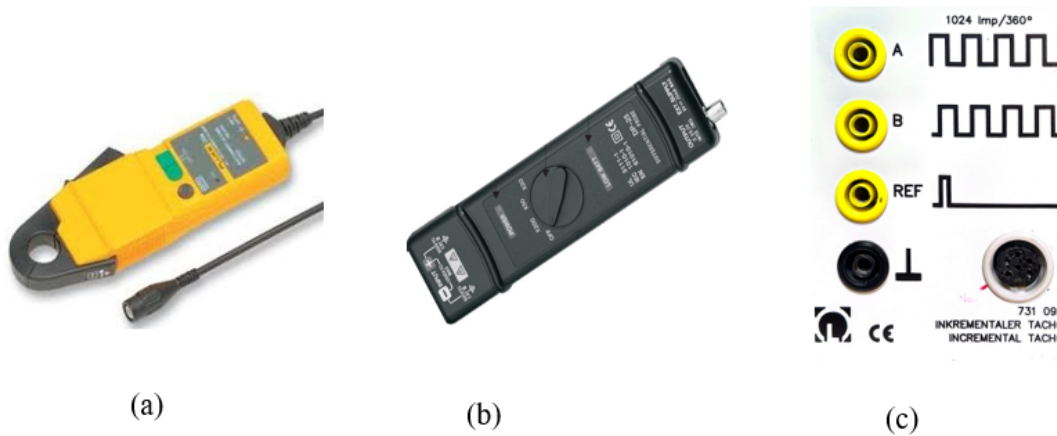


Figure 5.7: Sensors used in the experimental setup: (a) current sensor; (b) voltage sensor and (c) incremental sensor for rotor speed measurement.

A dedicated Digital I/O board is used to transmit the logic signals between the dSPACE

CLP1104 and the SEMIKRON inverter, ensuring reliable exchange of PWM commands, enable signals, and protection flags. Two DC sources are employed in the bench: a low-power supply delivering 15 V that feeds the inverter gate drivers and the Digital I/O circuitry, and a high-power DC source that energises the inverter DC bus and provides the main input power to the BLDC motor. On the mechanical side, the motor load is a DC motor coupled to a resistive charge, which acts as a controllable brake and allows the application of different load levels to the traction motor.

The complete laboratory test bench is depicted in Figure 5.8. The BLDC motor is supplied from the regulated DC link and is controlled by multiple algorithms running on the dSPACE CLP1104 platform. Various speed transition scenarios and load torque disturbances were introduced to evaluate the robustness and adaptability of the controller rigorously, and the motor parameters used in the experiments are detailed in [Appendix](#). The ControlDesk interface provides real-time visualisation of key quantities such as speed, torque, currents, and flux, enabling effective monitoring and analysis of controller performance under dynamic operating conditions.

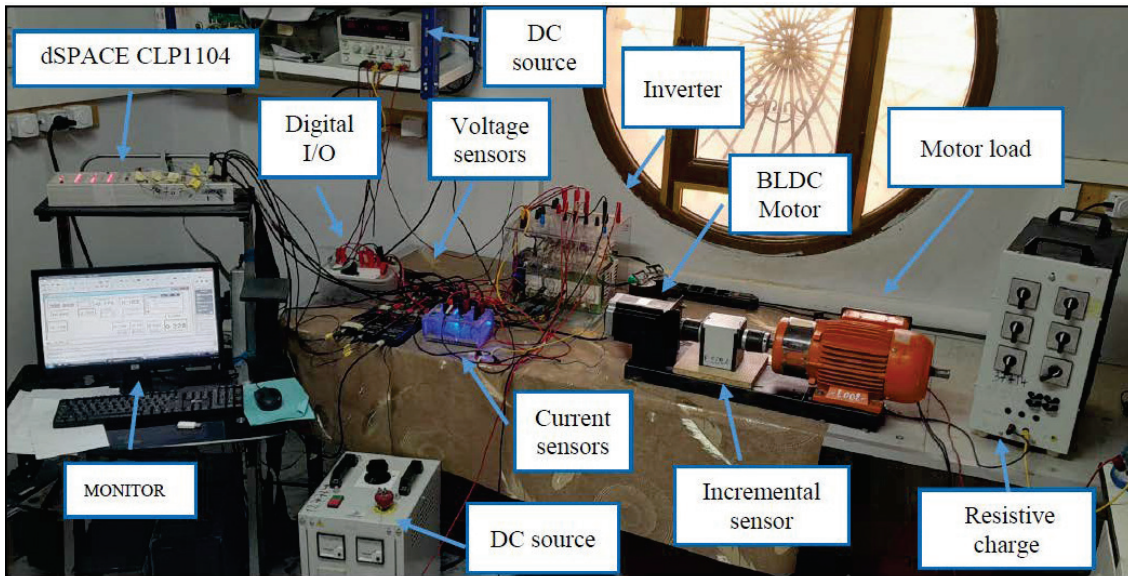


Figure 5.8: Real-time BLDC drive validation setup for the traction system.

5.3 Energy Management System in Power Sources Side Results

The proposed Energy Management System (EMS) is designed for an electric vehicle (EV) powered by a hybrid energy storage system (HESS) that combines a lithium-ion battery

pack and a supercapacitor (SC) module. The battery is intended to supply the average traction power over medium and long durations, whereas the SC is used as a high-power buffer to handle fast current transients and peak demands. The main electrical and physical characteristics of the two sources are summarized in Table 5.1.

Table 5.1: Characteristics of the battery and supercapacitor module.

Component	Parameter	Value
Battery	Technology	Lithium-ion (NMC)
	Nominal voltage (V)	12.8
	Capacity (Ah)	90
	Energy (Wh)	1150
	Internal resistance ($m\Omega$)	4
	Weight (kg)	10
Supercapacitor	Model name	BMOD0165
	Nominal voltage (V)	48
	Capacitance (F)	165
	Energy (Wh)	53
	Internal resistance ($m\Omega$)	6.3
	Weight (kg)	13.5

The lithium-ion battery parameters correspond to a representative NMC-based pack selected according to typical voltage levels, energy capacity, internal resistance, and gravimetric characteristics reported in the literature for electric vehicle applications in [1]. These parameters are consistent with commonly adopted lithium-ion configurations used in hybrid energy storage systems and provide a realistic basis for evaluating the proposed energy management strategy. The supercapacitor parameters are derived from experimental identification performed in the laboratory on the BMOD0165 module, following the methodology and characterization procedures detailed in previous work in [41]. This experimental identification ensures that the supercapacitor model accurately reflects its dynamic behavior under high-power transient operating conditions.

The objective of this section is to assess, in simulation only, the ability of the EMS to coordinate these two sources while maintaining a regulated DC bus voltage. To clearly decouple the EMS study from the traction control system analysed in Section 5.4, the BLDC motor and inverter are here replaced by an equivalent resistive load connected to the DC bus. The time-varying current drawn by this load is shaped to emulate the average current demand of the motor used in the later simulation, HIL, and experimental tests. The EMS simulation is performed in MATLAB/Simulink over a horizon of 140 s, during which several step changes in the requested DC current are imposed in order to excite the system under realistic dynamic operating conditions.

5.3.1 Simulation Results of the EMS

Figure 5.9 shows the current behaviour of the HESS and of the DC bus load throughout the 140 s test. The DC-bus load current i_{load} in Figure 5.9(a) follows a piecewise-constant profile with several step changes between approximately 1 A and 2.8 A. These steps represent different traction operating points such as low-speed cruising, moderate acceleration, and high-demand phases, and are used to evaluate the EMS response to abrupt variations in current demand.

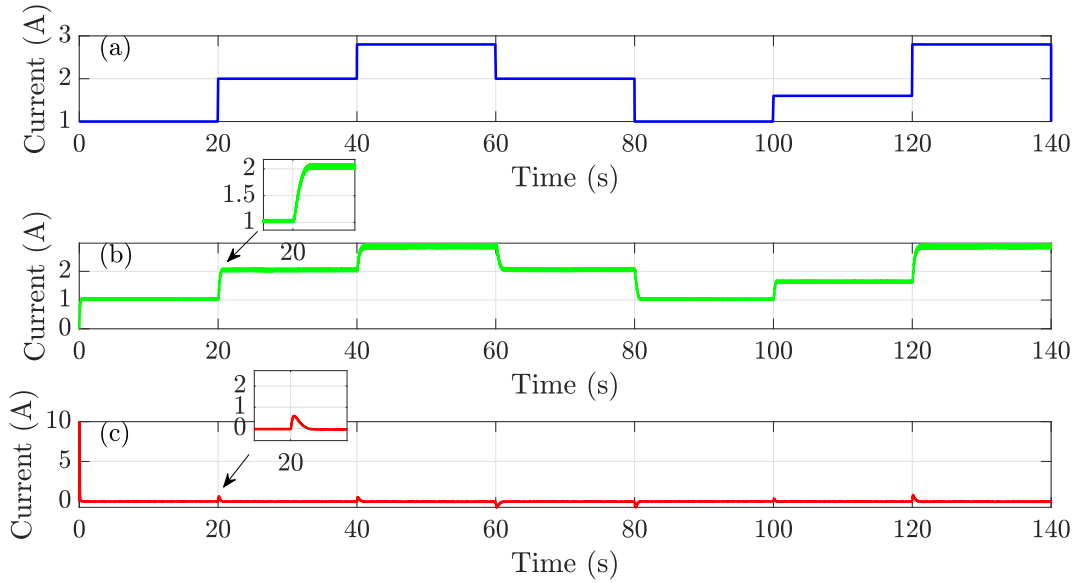


Figure 5.9: Current behaviour of the hybrid energy storage system:(a) DC bus load current i_{load} ; (b) battery current i_{battery} and (c) supercapacitor current i_{SC} .

The battery current, reported in Figure 5.9(b), exhibits smooth, slowly varying trajectories. After each load step, the battery current converges gradually towards a new steady-state level, without sharp peaks. This indicates that the EMS forces the battery to supply the low-frequency component of the power demand and prevents it from experiencing high di/dt values. The zoomed view contained in the figure highlights that the current response is essentially first-order in nature, which is beneficial for limiting electrochemical stress and thermal cycling in the lithium-ion cells.

In contrast, the SC current i_{SC} in Figure 5.9(c) is characterised by short, high-amplitude pulses concentrated around the load transitions, while remaining very small during the steady-state intervals. Each current step at the DC bus produces a corresponding transient in i_{SC} , with peak values significantly higher than the steady-state battery current. Physically, the SC rapidly injects or absorbs the difference between the new load current and the

slowly adapting battery current. Once the battery has settled to its new operating point, the SC current returns close to zero. This behaviour confirms the intended role of the SC as a high-power buffer that handles fast dynamics and peak power demands, thereby relieving the battery from such stress.

The impact of this current sharing on the energy content of each source is illustrated by the SOC trajectories in Figures 5.10 and 5.11. The battery SOC in Figure 5.10 decreases monotonically from 80 % to approximately 79 % over the 140 s interval, which corresponds to a net discharge of about 1 % of the nominal capacity. The SOC curve is smooth and almost linear, reflecting the predominance of low-frequency power exchange for the battery. This limited depth-of-discharge operation is particularly suitable for lithium-ion batteries, as it mitigates ageing effects and enhances cycle life. .

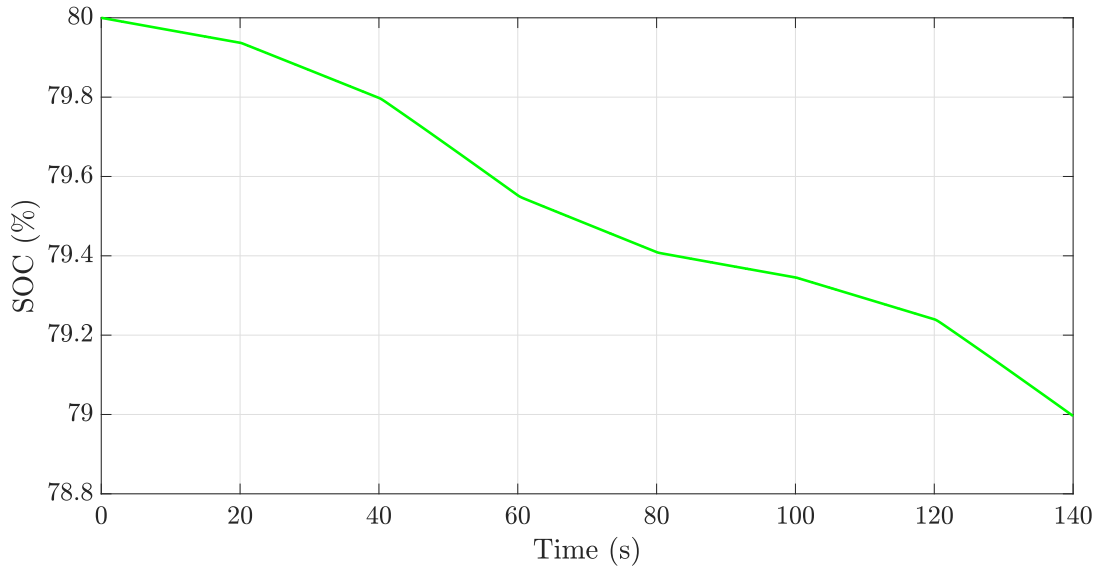


Figure 5.10: State-of-charge evolution of the battery during EMS simulation.

The SC SOC, shown in Figure 5.11, decreases from approximately 98.6 % to around 96.9 %. Although the absolute SOC variation remains limited, the relative change is clearly larger than that of the battery. This is coherent with the fact that the SC repeatedly supplies and absorbs energy during each transient phase, even if the average energy exchanged over the whole cycle is modest. The SOC remains within a mid-range window, which preserves a sufficient margin for future current peaks and guarantees safe operation of the module.

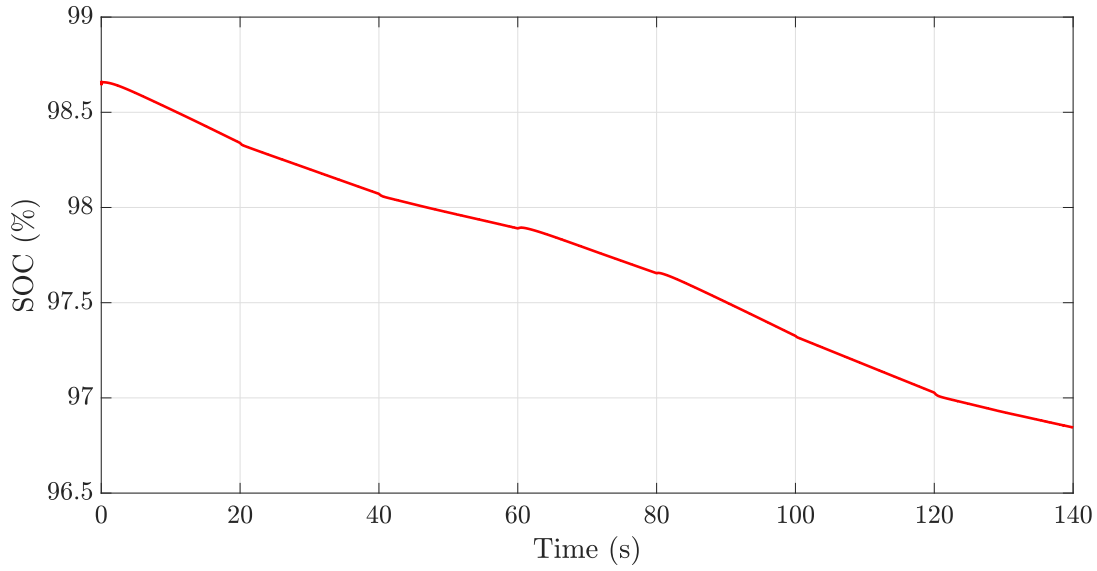


Figure 5.11: State-of-charge evolution of the supercapacitor during EMS simulation.

Figures 5.12 and 5.13 present the terminal voltages of the battery and the SC, respectively. The battery voltage in Figure 5.12 starts at around 12.17 V and exhibits a series of slow droops and recoveries associated with the changes in current demand. At the end of the test, the voltage reaches approximately 11.93 V. The transitions remain smooth and the voltage ripple around each step is limited, indicating that the battery is not subjected to abrupt current surges. This behaviour is consistent with the SOC evolution and further confirms that the EMS operates the battery in a mild regime.

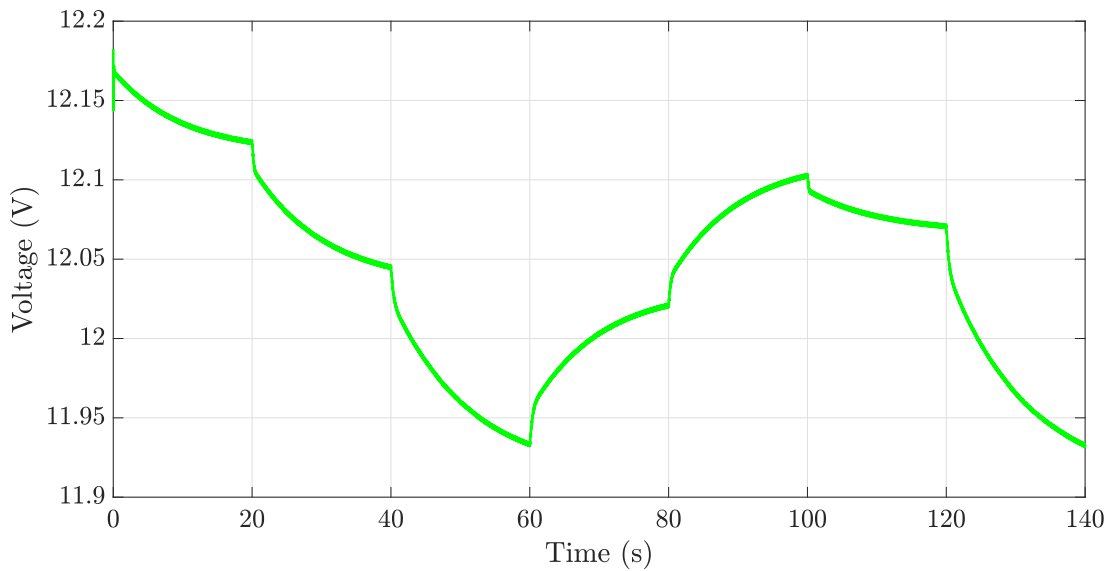


Figure 5.12: Battery terminal voltage during the EMS simulation.

The SC voltage in Figure 5.13 decreases from approximately 48 V to about 47.1 V over the same period. The voltage follows an almost linear trend with small kinks at the instants of load-current transitions, which correspond to the high-power pulses observable in Figure 5.9(c). This pattern is typical of capacitive storage devices whose voltage directly reflects the stored energy. The SC voltage remains well within the admissible operating range of the BMOD0165 module, demonstrating that the EMS avoids excessive depletion even though the SC is used intensively during transients.

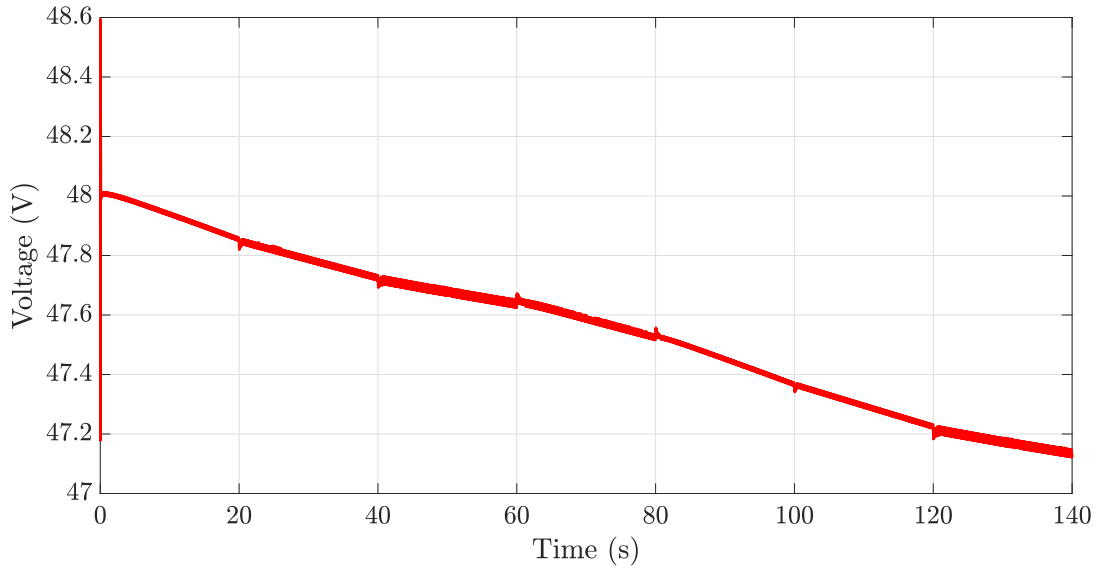


Figure 5.13: Supercapacitor terminal voltage during the EMS simulation.

The quality of the DC-link supply delivered by the HESS under the EMS is assessed in Figure 5.14, which shows the DC bus voltage V_{dc} over the entire 140 s test. After the initial start-up phase, the DC bus settles close to its reference value of 120 V and remains tightly regulated despite the repeated load-current steps. Small voltage dips and spikes are visible at the transition instants; however, their amplitude remains limited and the voltage rapidly returns to the nominal level. The inset in Figure 5.14 highlights a typical transient around a load step, where the bus voltage briefly deviates from the reference before being restored by the combined action of the SC and the DC bus regulator.

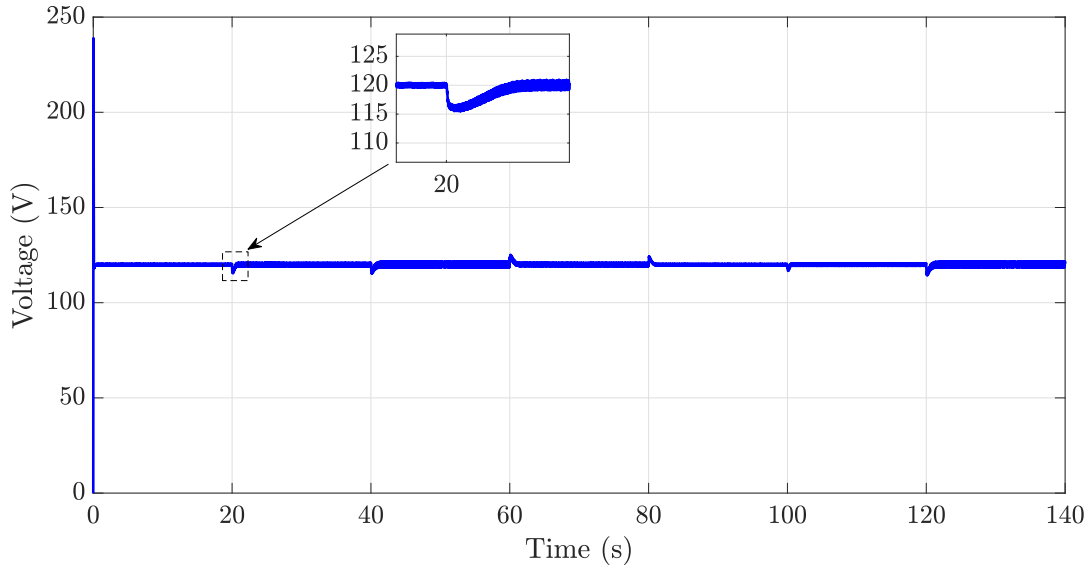


Figure 5.14: DC bus voltage regulation around 120 V during the EMS simulation.

5.3.2 Discussion of EMS Performance

The simulation results demonstrate that the proposed EMS provides an effective and physically consistent coordination of the battery and the SC under a load profile representative of EV traction demand. The current waveforms in Figure 5.9 clearly show the separation of roles between the two sources: the DC bus load current is subject to abrupt step changes, the battery current responds with smooth and slowly varying trajectories, and the supercapacitor current exhibits short, high-amplitude pulses at each transition. This confirms that the SC is responsible for supplying and absorbing the high-frequency component of the power demand, while the battery delivers the low-frequency and average components.

The SOC and voltage evolutions provide a complementary assessment. The battery SOC decreases by only about 1 % and its voltage remains within a narrow window around its nominal value, indicating that the battery operates in a conservative depth-of-discharge range with limited current stress. This operating regime is advantageous for preserving battery lifetime and thermal stability. In contrast, the SC undergoes larger relative SOC and voltage variations, in line with its role as a high-power buffer that frequently exchanges energy with the DC bus. Despite this more dynamic behaviour, the SC always remains within a safe SOC and voltage window, ensuring sufficient headroom for future transients.

The DC bus voltage response in Figure 5.14 confirms that the EMS is able to maintain a stiff DC link under the considered operating conditions. The voltage deviations at the instants of load-current changes are of short duration and limited magnitude. This behaviour is

essential to guarantee the correct operation of the traction inverter and BLDC motor. In the subsequent Section 5.4, the traction system is powered by a fixed 120 V DC source rather than by the EMS, in order to focus on the control-performance comparison between the different speed controllers. The results obtained here indicate that the proposed EMS and HESS configuration are capable of providing an equivalent DC-link quality under a current demand that resembles that of the real traction system.

Overall, the EMS simulations indicate that the adopted strategy enables:

- Effective sharing of power between the lithium-ion battery and the supercapacitor, with the SC handling transient power and the battery supplying the average energy.
- Reduced current stress and limited depth-of-discharge excursions for the battery, which is favourable for ageing and thermal behaviour.
- Safe and efficient operation of the SC within an appropriate SOC and voltage window, despite frequent charge/discharge events.
- Tight regulation of the DC bus voltage around 120 V over a 140 s load profile whose current demand emulates that of the BLDC traction system.

These results validate the suitability of the proposed EMS for integration with the advanced traction control system analysed in Section 5.4, where both simulation and experimental tests are carried out on the BLDC motor drive powered from a regulated 120 V DC source.

5.4 Traction System Side Results

In this section, both simulation and experimental results are presented to compare the performance of FOPI controllers optimized via PSO, BCO, and GWO with that of the proposed Adaptive Hybrid FOPI (A-HFOPI) controller, which combines fuzzy logic and the PSO algorithm. These comparisons are illustrated through shared graphs and tables to provide a clear visualization, particularly in the context of speed tracking and set-point regulation.

Importantly, the traction system simulations and experimental validation presented in this section are conducted independently of the EMS discussed in Section 5.2. In both the simulation and hardware setups, the traction inverter is powered by a fixed DC voltage source set to 120 V. The EMS is not active during this phase, as this section concentrates specifically on the core contribution of this work: the design, implementation, and performance evaluation of the advanced EV traction control system using the proposed A-HFOPI controller.

5.4.1 Simulation Results of the Traction System

The conventional PI controller is used as a baseline for performance comparison, as it remains the most widely adopted control strategy in industrial BLDC motor drives because of its simplicity and ease of tuning. Its limitations in nonlinear and dynamically changing conditions motivate the development and testing of more advanced approaches such as the metaheuristic-tuned FOPI and the proposed A-HFOPI controller.

The following subsections present the simulation results for: (i) offline tuning of the FOPI controllers, (ii) speed-response analysis under step changes in reference speed, (iii) online tuning behaviour of the adaptive controller, (iv) electrical behaviour of the BLDC drive, and (v) robustness against load-torque disturbances.

i) Offline tuning results:

The offline tuning with the specified conditions of the proposed MHA, whose configuration parameters are detailed in [Appendix](#), was performed to determine the optimal tuning parameters K_p , K_i , and λ . The optimization process utilized the PSO, BCO, and GWO algorithms, as well as a conventional PI controller tuned via the Ziegler-Nichols approach. The resulting controller parameters are summarized in Table 5.2.

Table 5.2: FOPI parameters based on the PSO, BCO, and GWO with the conventional PI.

Controller	K_p	K_i	λ
FOPI-PSO	3.3712	1.6218	2.4034
FOPI-BCO	1.8753	4.2351	2.7673
FOPI-GWO	6.7643	2.4695	2.1466
PI	0.6217	6.9517	-

Figure 5.15 shows the convergence graph of the ITAE index as a function of the iteration number for offline optimization via BCO, PSO, and GWO. The results show that PSO achieves the fastest convergence, reaching stability in just 33 iterations. This highlights the superior efficiency of PSO compared with BCO and GWO in minimizing the ITAE index within fewer iterations.

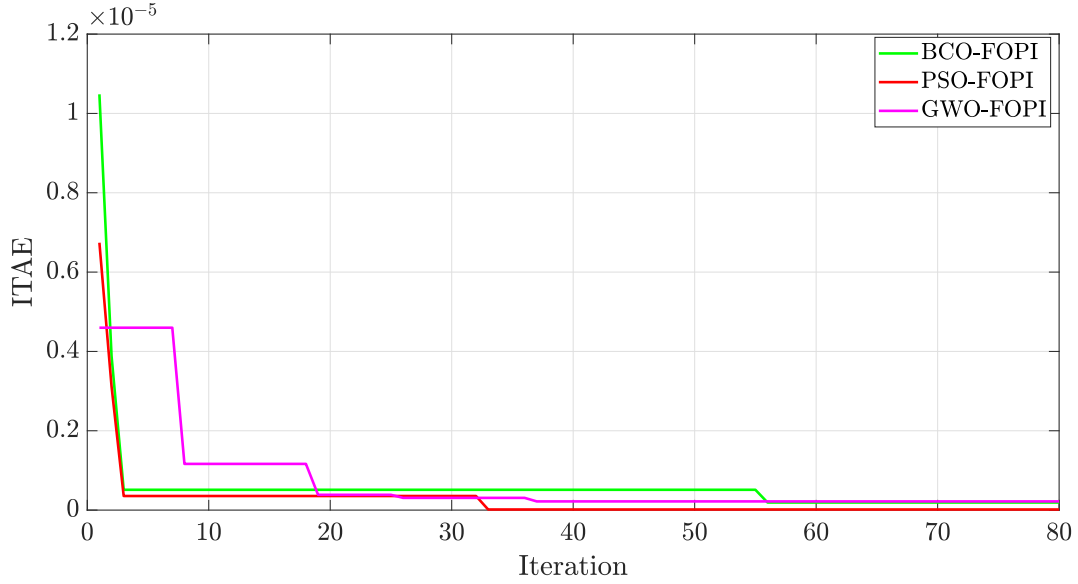


Figure 5.15: Convergence graph of ITAE indices versus iterations for offline tuning with PSO, BCO and GWO.

ii) Speed response results:

Figure 5.16 presents the speed response of the BLDC motor for different controllers under dynamic variations in the reference speed. Initially, at $t = 1s$, the reference speed decreases, followed by an increase at $t = 3s$. The response curves reveal distinct performance differences among the controllers.

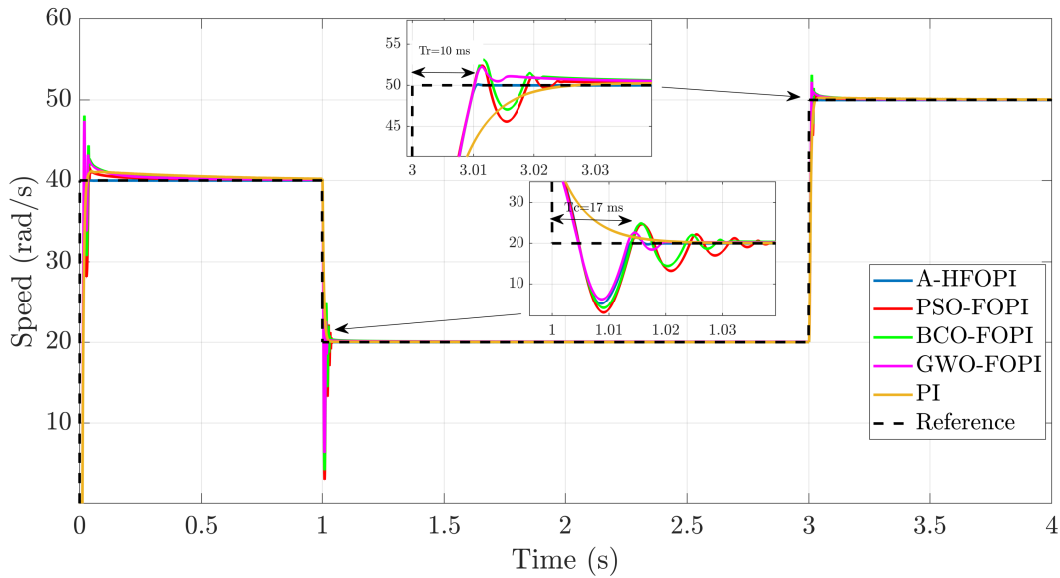


Figure 5.16: Speed response of the BLDC motor under different controllers.

The performance of various controllers was evaluated on the basis of key parameters, including the ITAE, IAE, Settling Time, Rise time, Overshoot, and Steady-State Error. A comprehensive comparison was conducted over the time interval from 1.5 to 2.5 seconds in Figure 5.16, where the ITAE, IAE, and steady-state error were calculated within this 1-second window. Moreover the settling time, rise time, and overshoot were evaluated at $t = 3s$. The results are summarized in Table 5.3, which highlights the advantages of the A-Hybrid FOPI-based Fuzzy-PSO controller.

Table 5.3: Performance indices of the various controllers under step changes in reference speed. Abbreviations: S T – Settling Time, R T – Rise Time, Os – Overshoot, S S E – Steady-State Error, ITAE – Integral Time Absolute Error, IAE – Integral Absolute Error.

Controller	S T (s)	R T (s)	Os (%)	S S E	ITAE	IAE	Total Indices
A-HFOPI	0.25	1.2 e-2	0.36	5.20 e-4	1.14 e-2	2.30 e-3	1.37 e-2
FOPI-PSO	0.43	1.0 e-2	8.16	1.26 e-2	4.88 e-1	1.04 e-1	5.92 e-1
FOPI-BCO	0.29	1.0 e-2	10.33	7.92 e-3	4.41 e-1	9.59 e-2	5.37 e-1
FOPI-GWO	0.49	1.0 e-2	7.43	6.07 e-3	4.05 e-1	8.81 e-2	4.93 e-1
PI	0.68	2.6 e-2	0.86	6.97 e-3	3.87 e-1	9.00 e-2	4.77 e-1

The A-HFOPI controller demonstrated superior performance with faster convergence and significantly lower performance indices, achieving an ITAE of 0.0114, an IAE of 0.0023, and a total index sum of 0.0137. In terms of the transient response, the proposed controller exhibited the fastest tracking response, with a settling time of 0.25 s and a rise time of 0.012 s, a minimal overshoot of 0.36%, and a very low steady-state error of 0.0005207. Moreover, the controller significantly reduced the error indices, improving the ITAE and IAE by more than 97.05% and 97.79%, respectively, compared with those of the other controllers. These results confirm the effectiveness of the A-HFOPI approach in achieving precise and efficient speed control for BLDC motors.

iii) Online tuning results:

To highlight the self-tuning capability of the proposed A-HFOPI controller during the same speed-change test, Figures 5.17 and 5.18 show the online evolution of the proportional and integral parameters K_p , K_i , and the fractional order λ . The FOPI controller parameters are adjusted in discrete steps at each reference-speed transition while remaining bounded, which contributes to the improved transient behaviour observed in Figure 5.16.

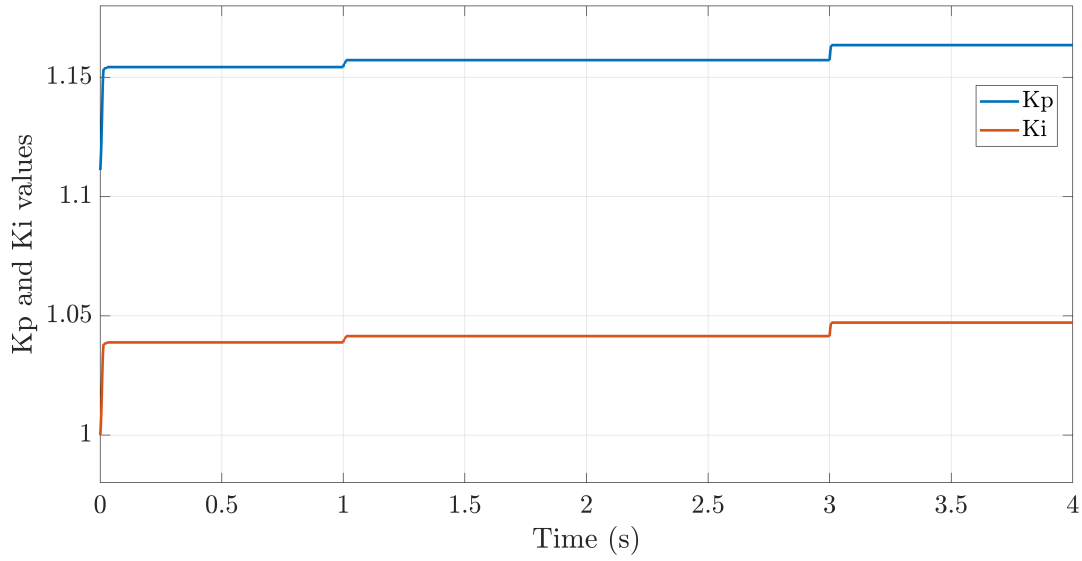


Figure 5.17: Adaptive evolution of K_p and K_i for the A-HFOPI controller during the speed-change test.

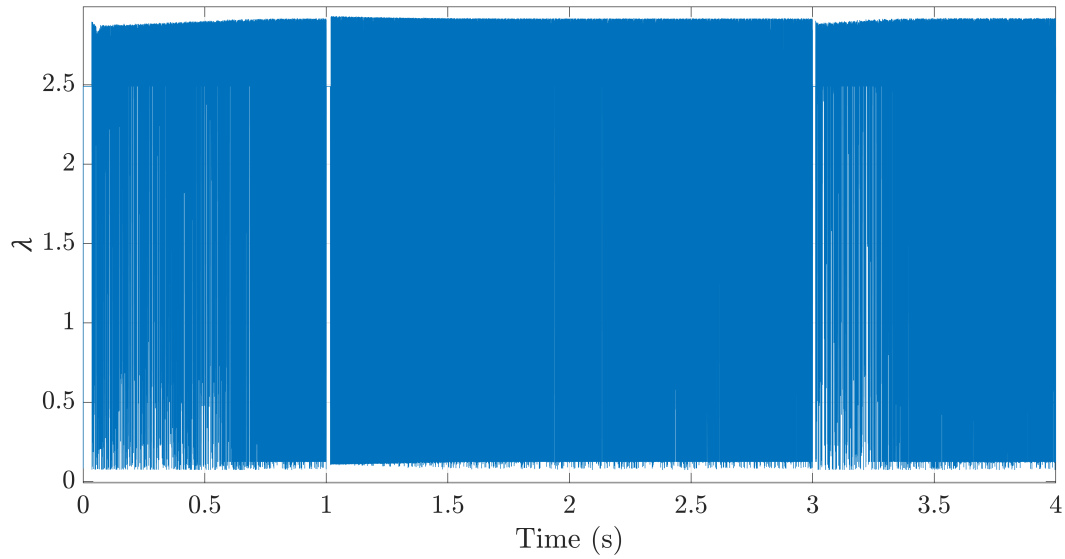


Figure 5.18: Adaptive evolution of the fractional order λ for the A-HFOPI controller during the speed-change test.

The proposed controller exhibits superior performance, characterized by a faster convergence time, reduced overshoot, and minimal steady-state error. The PI controller, as well as the optimized controllers (PSO, BCO, GWO), successfully converge to the reference speed. However, the optimized controllers show varying degrees of transient response performance, with some experiencing greater overshoot or slower adaptation. Among them, the A-HFOPI

controller demonstrates the fastest adaptation to changes, ensuring improved robustness and stability.

iv) Electrical motor behaviour results:

To complement the speed-tracking analysis, Figures 5.19, 5.20, and 5.21 illustrate the electrical behaviour of the BLDC drive under the proposed A-HFOPI controller for the same test conditions. The plots show the phase back-EMF waveforms, the stator flux trajectory in the α - β plane, and the stator phase currents, confirming the correct excitation and commutation of the motor.

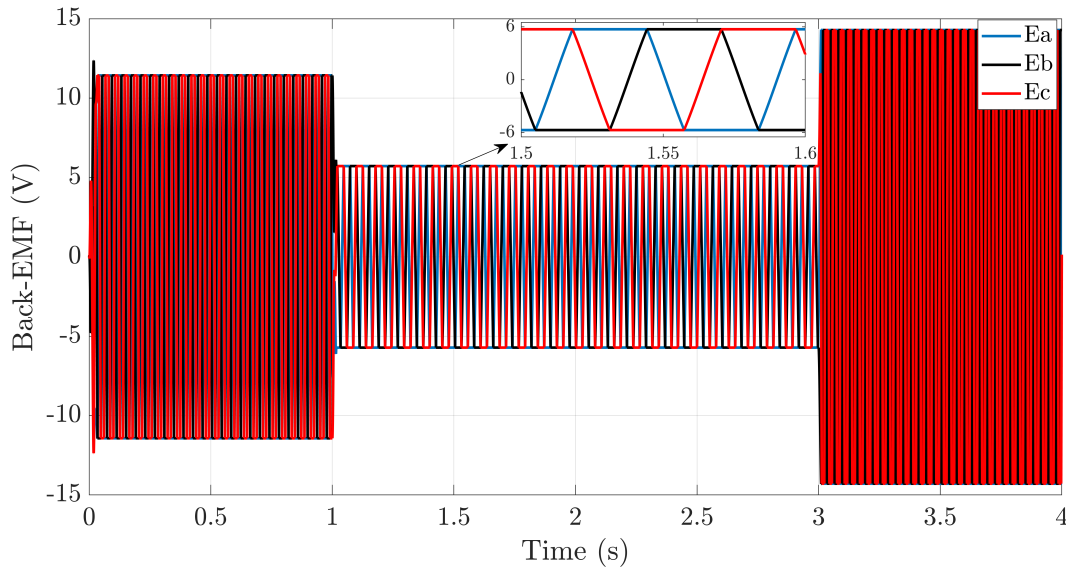


Figure 5.19: Phase back-EMF waveforms of the BLDC motor under the A-HFOPI controller.

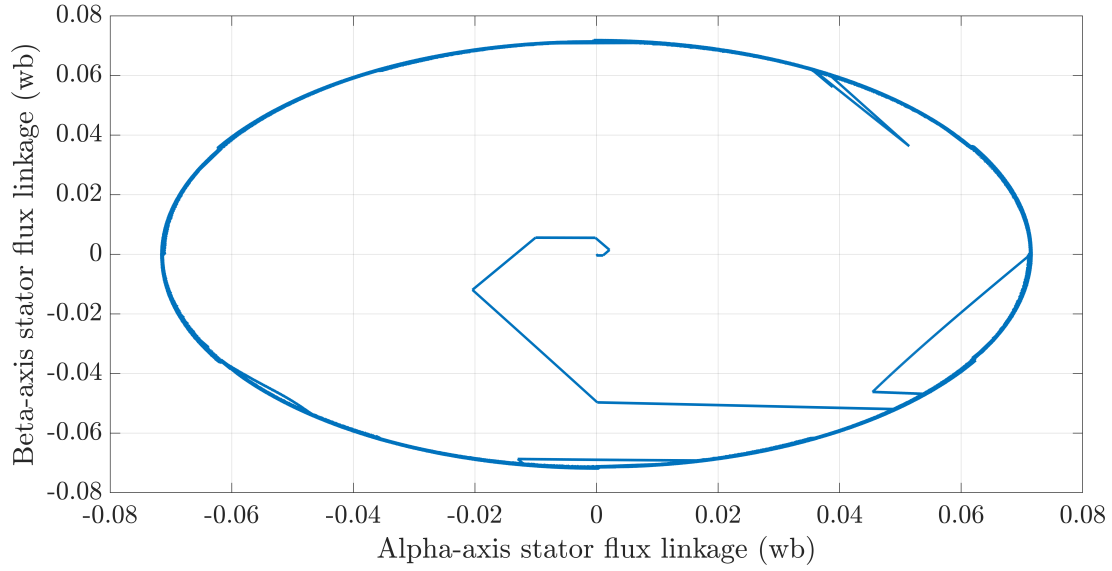


Figure 5.20: Stator flux trajectory in the α - β plane for the A-HFOPI-controlled BLDC drive.

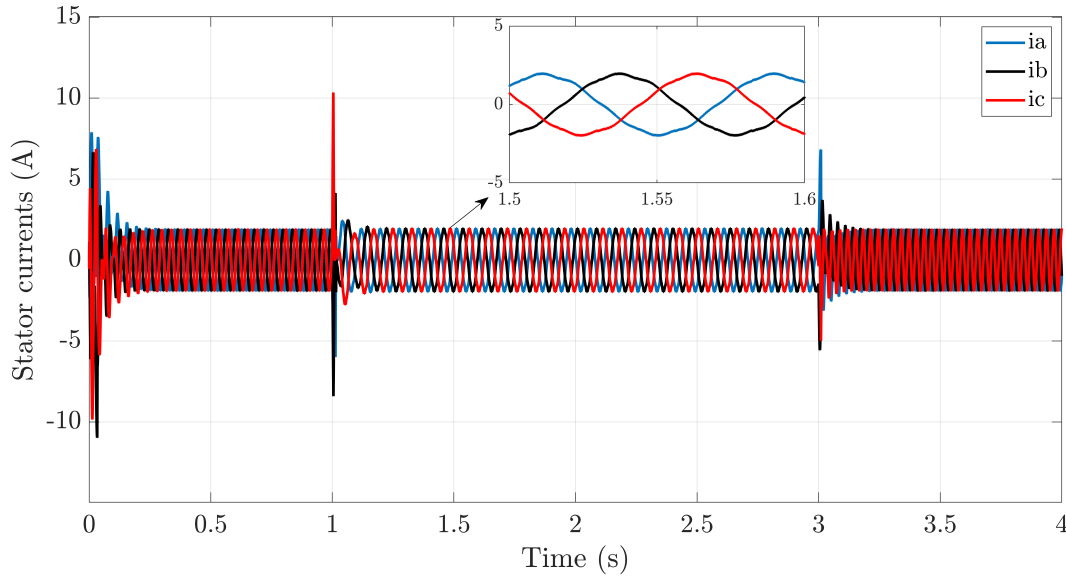


Figure 5.21: Stator phase currents of the BLDC motor with the A-HFOPI controller.

v) Load torque disturbance result:

Figure 5.22 illustrates the speed-tracking performance of the recommended controllers under disturbance conditions. The results indicate that both FOPI-based MHA controllers and conventional PI controllers struggle to accurately track the desired speed, with FOPI-based MHA controllers requiring the most time to converge after a perturbation occurs at the chosen time $t=3$ s. In contrast, the A-HFOPI controllers significantly outperform them,

demonstrating superior capability in quickly returning to the set-point value following the onset of an external disturbance. Furthermore, systems utilizing A-HFOPI controllers require significantly less recovery time than their counterparts, highlighting their efficiency and robustness in maintaining the desired performance despite disturbances.

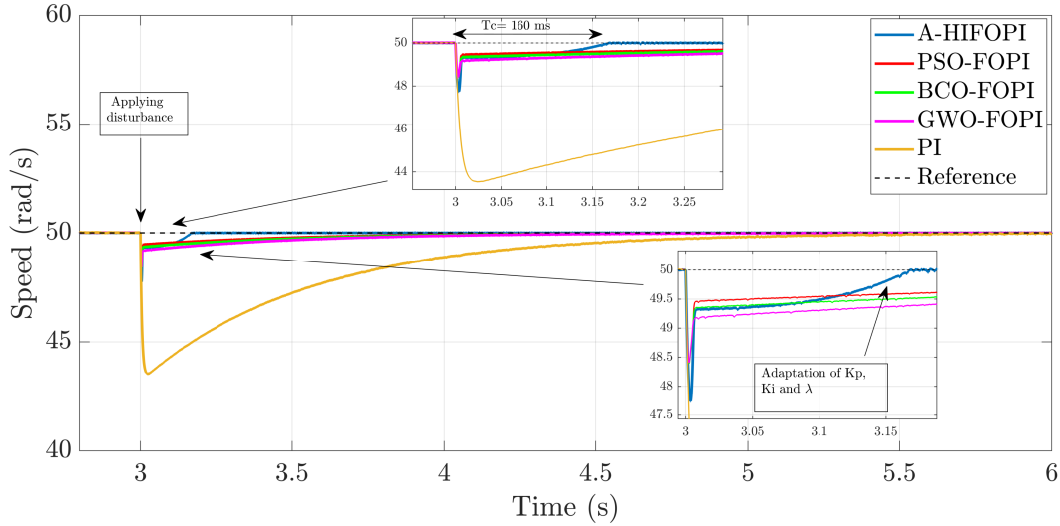


Figure 5.22: Case of applying an external disturbance with a torque load of $T_l = 0.8Nm$.

5.4.2 HIL Results of the Traction System

Using the HIL configuration described in Section 5.2.1, the different controllers (PI, FOPI-PSO, FOPI-BCO, FOPI-GWO, and the proposed A-HFOPI) were implemented in real time to assess their performance under variable operating conditions. The same speed-change and disturbance scenarios as in the pure simulations were reproduced, which allows a direct comparison between simulated results and HIL-based responses. Three test cases were considered: (i) speed-response tests, (ii) electrical behavior of the motor, and (iii) the application of a constant load torque disturbance.

i) Speed-response results:

To evaluate the dynamic tracking capability of each controller, a first experiment was carried out in which the reference speed was subjected to a step change from 30 rad/s to 80 rad/s. Figure 5.23 presents the corresponding motor speed trajectories obtained in HIL. All controllers are able to follow the reference; however, the A-HFOPI controller exhibits the fastest rise time, very small overshoot, and rapid convergence to the new steady-state value.

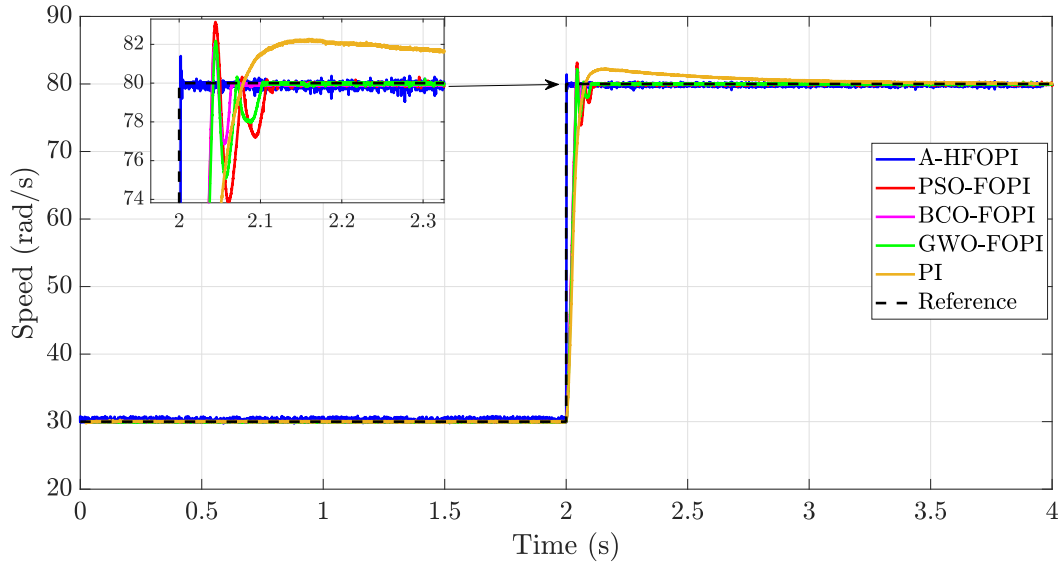


Figure 5.23: Motor speed response during a sudden speed increase.

A second experiment was performed to assess the behavior during a deceleration phase, in which the reference speed was reduced from the high-speed operating point back to 30 rad/s. The resulting responses are shown in Figure 5.24. The A-HFOPI controller again provides the most favorable dynamics, with a smooth and well-damped transition and negligible steady-state error, whereas the other controllers exhibit slower convergence and more pronounced transient deviations.

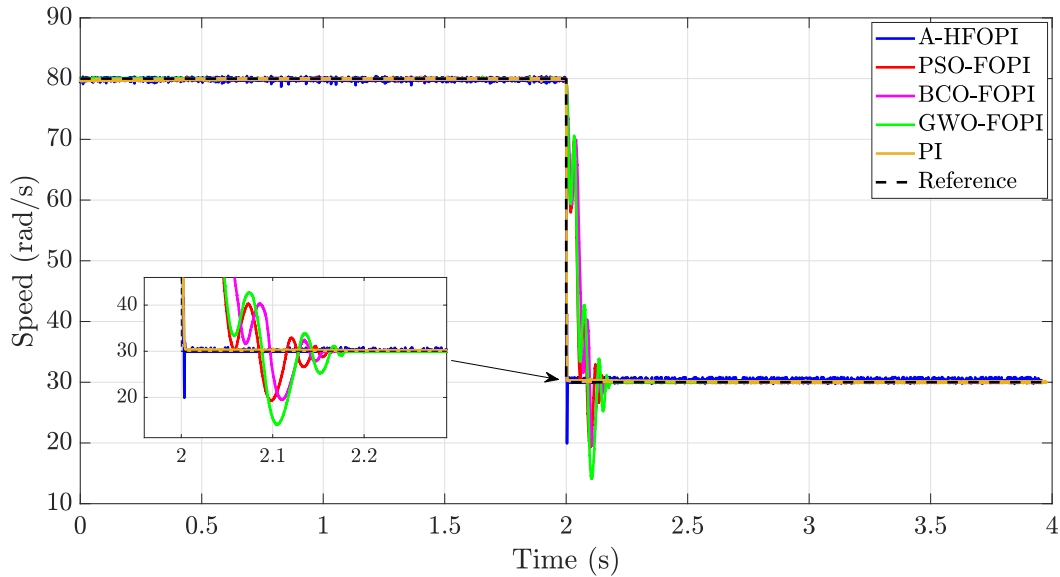


Figure 5.24: Motor speed response during a sudden speed decrease.

ii) Electrical motor behavior results:

In order to examine the electrical behavior of the BLDC drive under the proposed control strategy, the stator phase currents and the back-EMF were recorded during the speed-increase experiment. Figure 5.25 shows the measured stator current, which exhibits the expected quasi square-wave waveform with superimposed switching ripple, confirming proper operation of the DTC-based inverter and the commutation sequence.

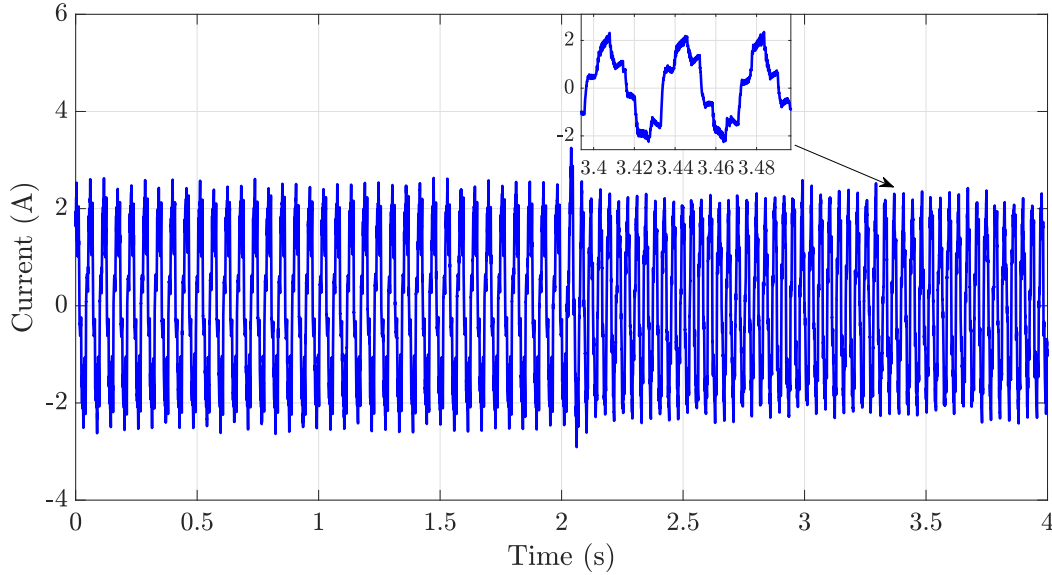


Figure 5.25: Wave-square stator current during the increasing-speed HIL test.

Figure 5.26 presents the corresponding phase back-EMF. The voltage waveform preserves its trapezoidal shape over the whole test, with an amplitude that increases consistently with the rotor speed. This result confirms that the electromagnetic behavior of the BLDC motor is correctly reproduced in the HIL platform and remains compatible with the assumptions of the adopted control model.

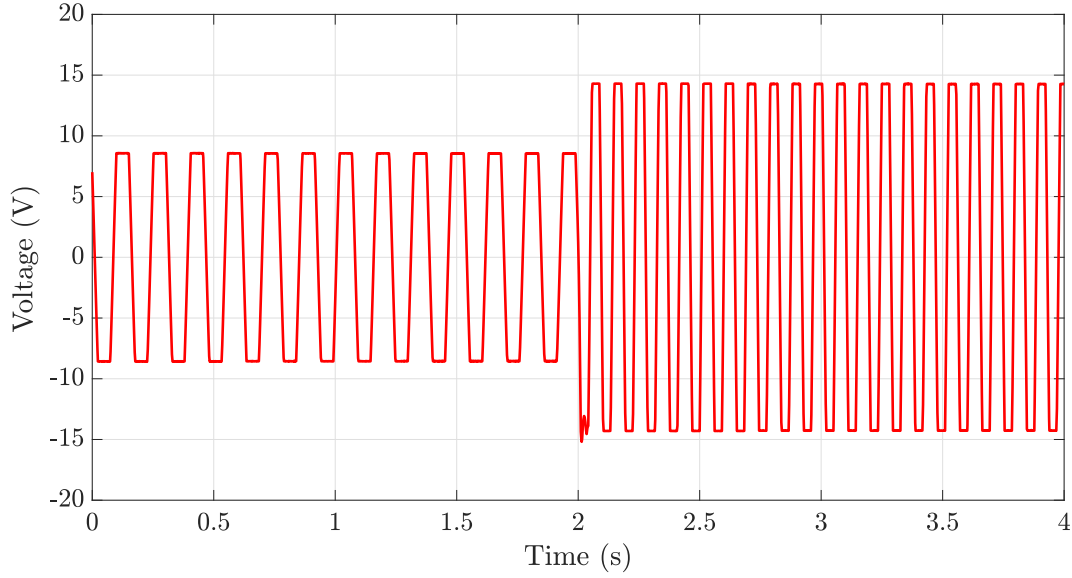


Figure 5.26: Trapezoidal back-EMF during the increasing-speed HIL test.

iii) Load torque disturbance result:

A third HIL experiment was carried out to evaluate the robustness of the controllers with respect to external disturbances. In this test, a constant load torque of $T_l = 0.8$ Nm was applied to the motor shaft while the reference speed was kept constant. The resulting speed responses are shown in Figure 5.27. The A-HFOPI controller maintains the desired speed with only a small transient deviation at the disturbance onset, demonstrating strong disturbance rejection and good adaptability. The metaheuristic-based FOPI controllers exhibit larger deviations and longer recovery times, whereas the conventional PI controller achieves acceptable but less performant disturbance attenuation compared with A-HFOPI.

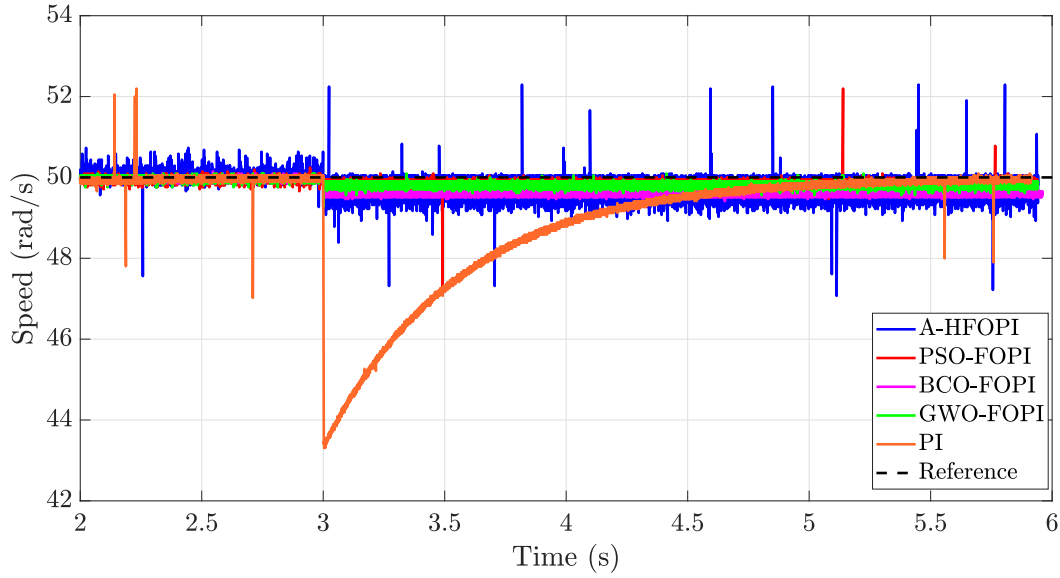


Figure 5.27: HIL test for speed tracking under an external torque load of $T_l = 0.8$ Nm.

5.4.3 Real-Time Experimental Results

Using the real test bench setup described in Section 5.2.2, the proposed control strategy was experimentally implemented on the BLDC motor under operating conditions representative of electric vehicle applications. The reference speed profile was derived from the New European Driving Cycle (NEDC), which has a nominal duration of 1180 s, as shown in Figure 5.28. Owing to the memory and computation limits of the dSPACE CLP1104 system, the experimental tests were carried out over a truncated interval of 1000 s while preserving the main acceleration, cruising, and deceleration phases of the cycle.

The following subsections present the experimental results for: (i) speed-response tests, (ii) online tuning behaviour of the adaptive controller, (iii) load torque disturbance and electromagnetic torque ripple, and (iv) tracking performance under the NEDC together with quantitative performance indices.

i) Speed-response results:

To evaluate the transient behaviour of the different controllers, an acceleration test was performed in which the reference speed was changed from standstill to a constant target value of 40 rad/s at $t = 2$ s. All controllers were commanded to track the same reference while the BLDC motor operated without external mechanical load.

Figure 5.29 shows the experimental speed responses for the PI, FOPI-PSO, FOPI-BCO, FOPI-GWO, and proposed A-HFOPI controllers. All controllers are able to reach the tar-

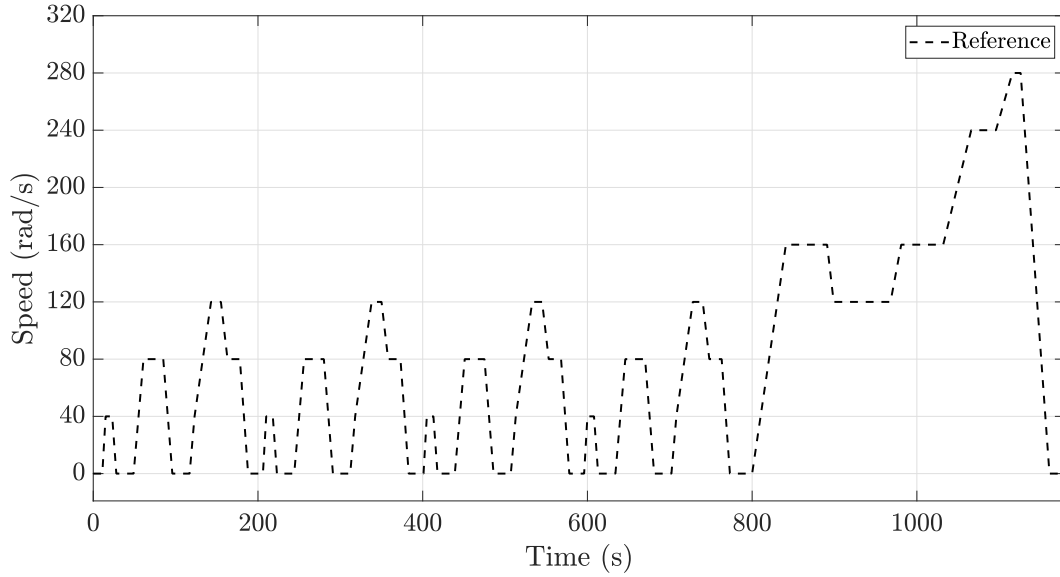


Figure 5.28: New European driving cycle profile (NEDC).

get speed; however, differences appear in terms of rise time and small residual oscillations. The A-HFOPI controller exhibits a fast convergence to the reference with limited overshoot and reduced oscillatory behaviour, whereas the fixed-parameter controllers require a longer settling time and present more pronounced fluctuations around the steady-state speed.

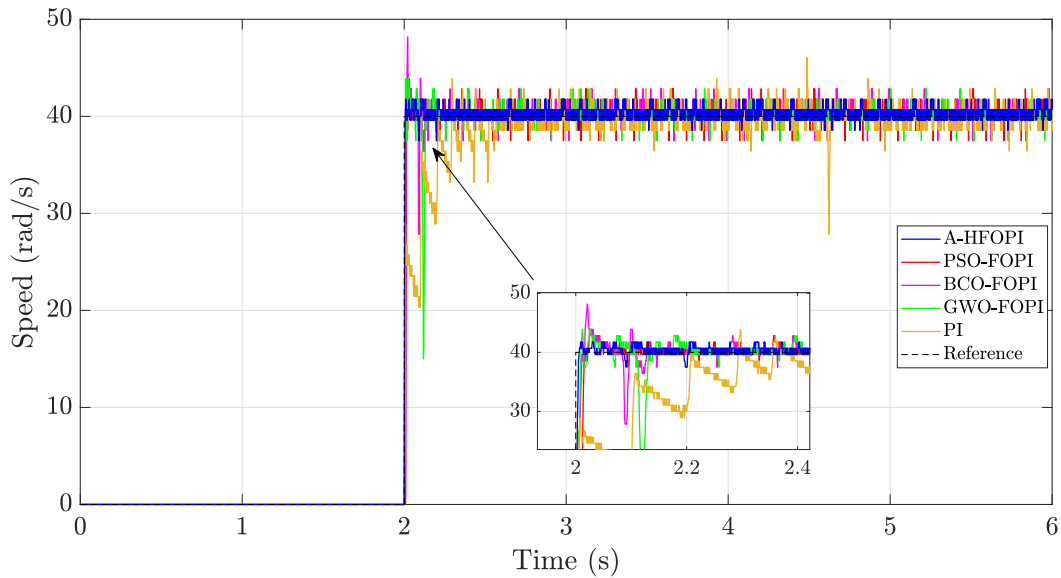


Figure 5.29: Experimental results of the speed transition from zero to a targeted speed.

ii) Online tuning results:

The adaptive behaviour of the proposed controller during the same acceleration experiment is analysed through the time evolution of the proportional and integral gains and the fractional order. In this test, the A-HFOPI controller updates K_p , K_i , and λ online according to the hybrid fuzzy-PSO tuning mechanism described in Chapter 4.

Figure 5.30 depicts the trajectories of K_p and K_i . Before the speed step ($t < 2$ s), the gains remain at their initial low values because the motor operates at zero speed. Immediately after the reference change, both gains increase rapidly and then evolve smoothly towards quasi-stationary levels as the PSO-based adaptation refines the parameters. This behaviour indicates that the controller reacts strongly to the large initial error and then progressively adjusts the gains to maintain stable tracking.

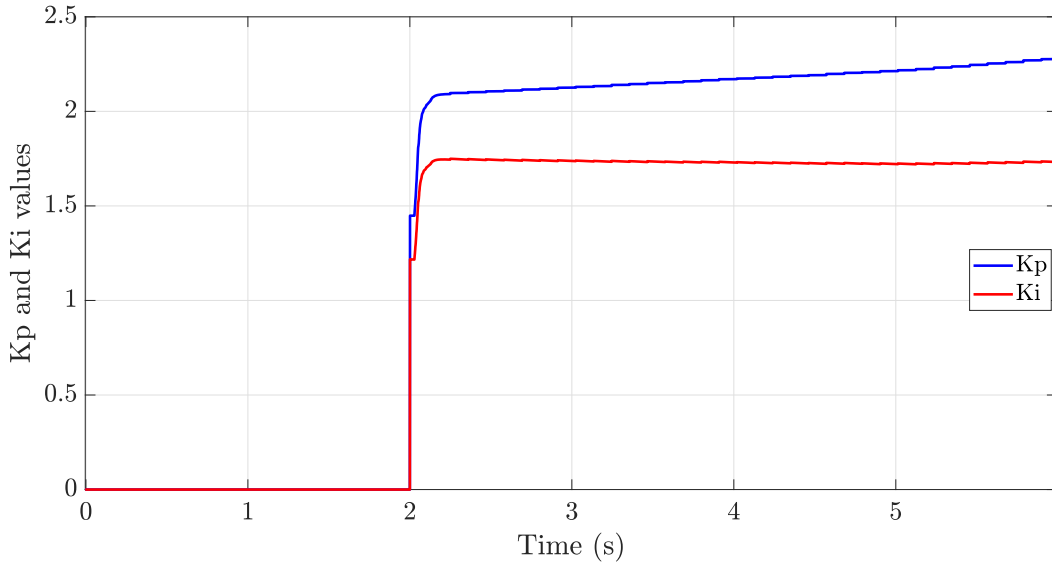
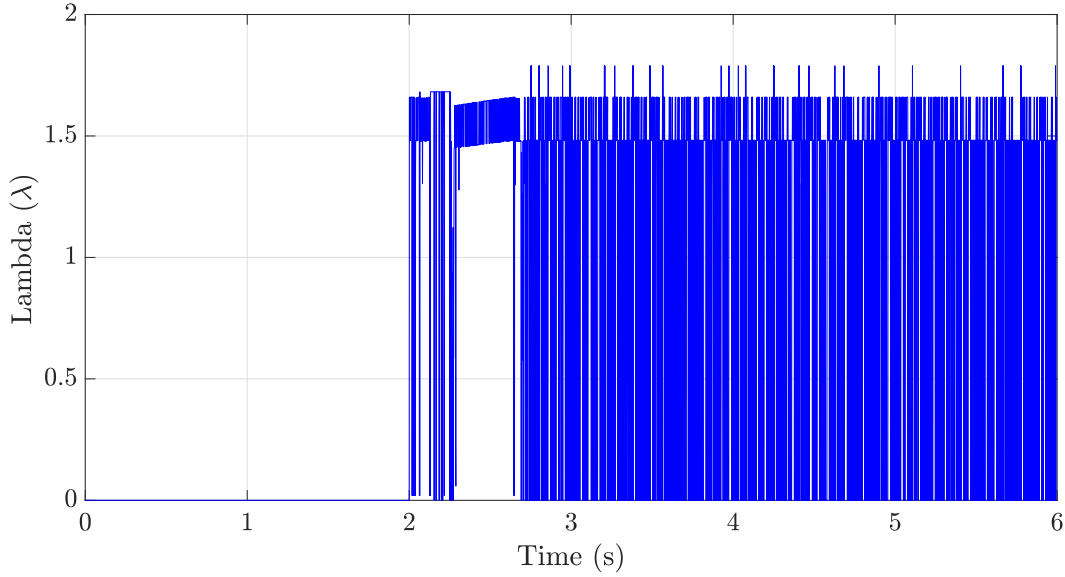


Figure 5.30: Adaptive values of K_p and K_i in the acceleration experiment test.

Figure 5.31 shows the corresponding adaptation of the fractional integral order λ . After the speed step, λ rapidly moves from its initial value and then fluctuates within a bounded interval around approximately 0–1.7. These variations reflect the action of the fuzzy inference system, which modifies λ based on the instantaneous error and its derivative in order to shape the transient and steady-state behaviour of the controller. Despite the high update frequency, λ remains confined within the prescribed limits, which is consistent with a stable adaptive process.

Figure 5.31: Adaptive λ in the acceleration experiment test.

iii) Load torque disturbance and electromagnetic torque ripple results

To evaluate the disturbance-rejection capability and electromagnetic torque quality of the proposed controllers, an external load torque was applied using a DC machine coupled to a variable resistive load, as described in Section 5.2.2. The applied load torque was determined experimentally from the electrical measurements of the DC motor. For a resistive load of $R = 2.6 \, \Omega$ and an armature current of $I = 4.30 \, \text{A}$, the electrical power is given by:

$$P = RI^2 = 48.07 \, \text{W}$$

With a measured angular speed of $\omega = 40.05 \, \text{rad/s}$, the corresponding load torque is obtained as:

$$T_l = \frac{P}{\omega} = 1.20 \, \text{Nm}$$

Figure 5.32 presents the speed-tracking responses when this load torque is applied at $t = 2 \, \text{s}$ while the reference speed is maintained at about $40 \, \text{rad/s}$. The A-HFOPI controller reaches the new steady state in approximately $0.45 \, \text{s}$, whereas PSO-FOPI, BCO-FOPI, GWO-FOPI, and PI settle in about $0.75 \, \text{s}$, $0.78 \, \text{s}$, $0.80 \, \text{s}$, and $1.06 \, \text{s}$, respectively. The PI controller exhibits the largest transient speed drop after the load application, while the optimized FOPI-based controllers, including A-HFOPI, limit the speed deviation and provide smoother recovery.

The impact of the same torque disturbance on the electromagnetic torque quality is examined in Figure 5.33, which displays the torque ripple signals obtained for all controllers under $T_l = 1.2 \, \text{Nm}$. After the transient phase, each controller exhibits a characteristic ripple level

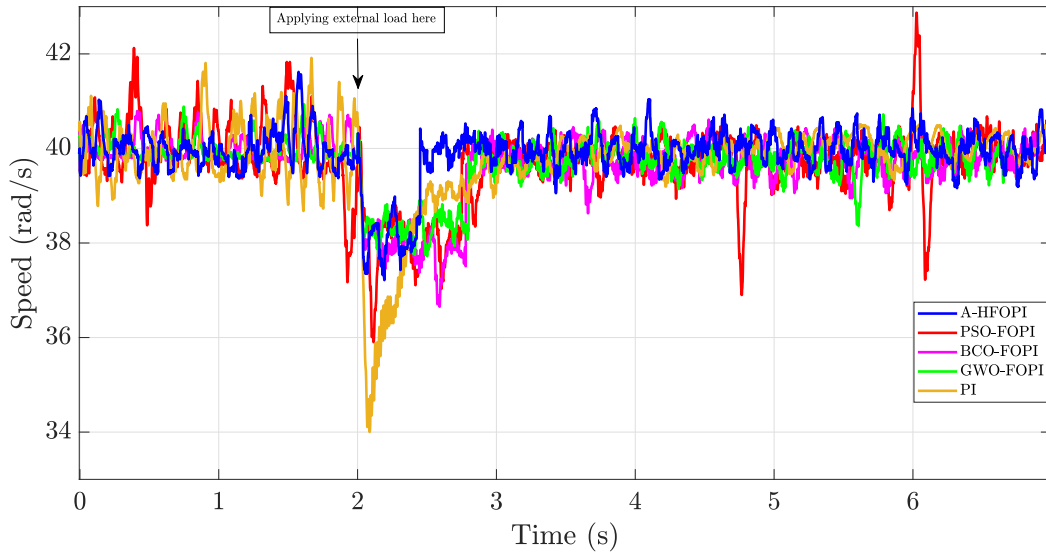


Figure 5.32: Experimental test of speed tracking under an external torque load of $T_l = 1.2$ Nm.

and spectral content. The conventional PI controller produces the smallest visible ripple amplitude, whereas the metaheuristic-based FOPI controllers, and particularly A-HFOPI, generate slightly higher but still bounded oscillations.

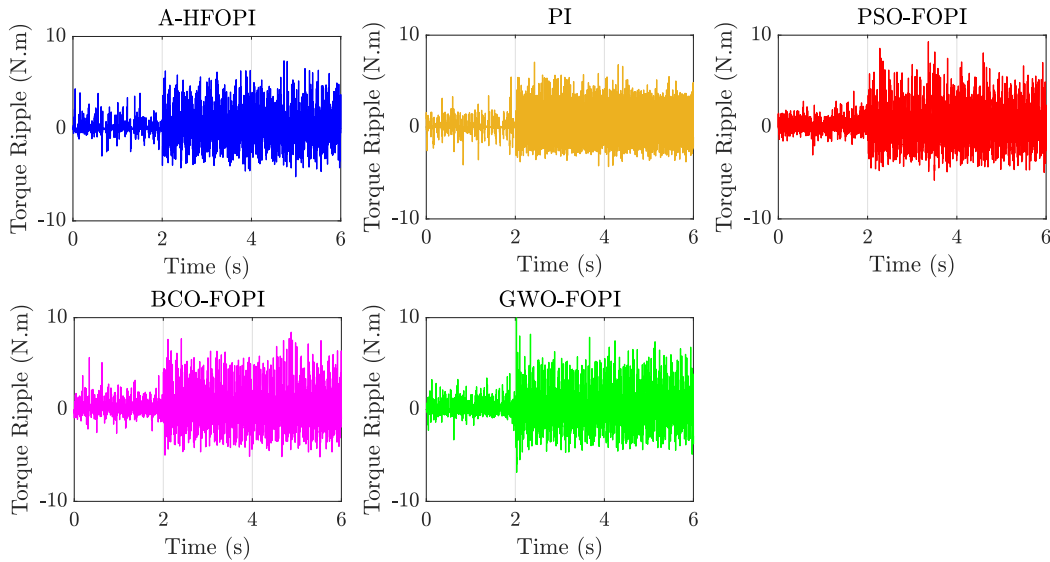


Figure 5.33: Experimental test of the torque ripple under an external torque load of $T_l = 1.2$ Nm.

To quantify these observations, Table 5.4 reports the Root Mean Square (RMS) values of the torque ripple for $t > 2$ s. The PI controller achieves the lowest RMS value (1.6701 Nm),

followed closely by the proposed A-HFOPI controller (1.7221 Nm). The FOPI-BCO and FOPI-GWO controllers present nearly identical ripple levels, while FOPI-PSO yields the highest RMS value in this comparison. These results indicate a trade-off between the torque smoothness and the disturbance-rejection speed, with A-HFOPI achieving a torque ripple comparable to PI while providing faster recovery in Figure 5.32.

Table 5.4: RMS values of torque ripple for $t > 2$ s under load of $T_l = 1.2$ Nm.

Controller	Torque Ripple RMS (Nm)
PI (Conventional)	1.6701
A-HFOPI (Proposed)	1.7221
FOPI-BCO	1.8852
FOPI-GWO	1.8876
FOPI-PSO	1.9071

iv) NEDC tracking performance and quantitative assessment:

The controllers were assessed under the complete NEDC-based speed profile to analyse their behaviour over a long-duration driving scenario with multiple acceleration, cruising, and deceleration segments. In this test, each controller was required to track the reference speed trajectory derived from Figure 5.28 while the BLDC motor operated with the same mechanical configuration as in the previous experiments.

Figure 5.34 presents the measured speed responses of all controllers under the NEDC. The A-HFOPI controller tracks the reference with small deviations throughout the cycle, whereas the metaheuristic-based fixed-parameter FOPI controllers exhibit slightly larger errors and slower adaptation during rapid speed changes. The conventional PI controller shows the largest deviations and more pronounced oscillations, particularly during high-gradient segments of the driving cycle.

A quantitative comparison was performed using the performance indices listed in Table 5.5. The Integral Time Absolute Error (ITAE), Integral Absolute Error (IAE), steady-state error (SSE), and overshoot were evaluated over the interval $t \in [842, 843]$ s, with the overshoot computed at $t = 841$ s. A composite “Total Indices” measure was obtained by summing the ITAE and IAE contributions for each controller.

The A-HFOPI controller attains the lowest overshoot (0.29 %), the smallest steady-state error (0.24), and the lowest ITAE and IAE values (51.97 and 6.16×10^{-2} , respectively), leading to the smallest total index (52.03). The PI controller presents the highest overshoot (1.98 %) and the largest ITAE and IAE values, which results in the highest total index.

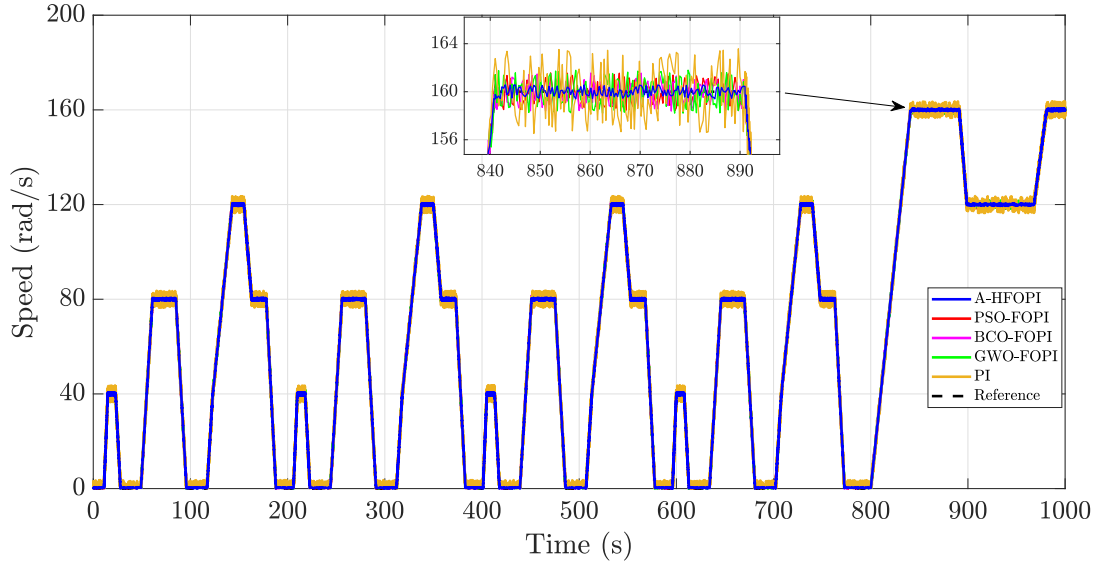


Figure 5.34: Speed response of the BLDC motor under the NEDC.

Table 5.5: Performance indices of different controllers in the experiments; Abbreviations: Os – Overshoot, S S E – Steady-State Error, ITAE – Integral Time Absolute Error, IAE – Integral Absolute Error.

Controller	Os (%)	S S E	ITAE	IAE	Total Indices
A-HFOPI	0.29	0.24	51.97	6.16 e-2	52.03
FOPI-PSO	0.62	0.53	78.59	9.31 e-2	78.68
FOPI-BCO	0.47	0.54	124.75	1.47 e-1	124.89
FOPI-GWO	0.70	0.90	177.79	2.10 e-1	178.00
PI	1.98	1.38	278.98	3.30 e-1	279.31

The FOPI-PSO, FOPI-BCO, and FOPI-GWO controllers provide intermediate performance, with total indices between those of A-HFOPI and PI. Among the fixed-parameter FOPI controllers, FOPI-PSO exhibits the lowest total index (78.68). Overall, the experimental results under the NEDC indicate that the adaptive A-HFOPI controller offers the most favourable compromise between tracking accuracy, transient behaviour, and long-term error accumulation in the considered experimental framework.

5.5 Comparative Analysis

To situate the proposed control strategy within the context of recent advancements, a comparative analysis of hybrid fuzzy–metaheuristic controllers for motor speed regulation is presented in Table 5.6. The table outlines key characteristics of each approach, including the type of application, control structure (parallel or cascaded), computational complexity, re-

ported performance benefit, and the level of experimental validation.

Table 5.6: Relevant fuzzy–metaheuristic motor control approaches from the literature, illustrating common architectures and validation levels.

Strategy	App. Type	Archit.	Complex.	Perf. Benefit	Implem.
ANFIS Con- troller [159]	DC Motor	Cascaded	Medium	Zero overshoot, fast settling	Real-time (dSPACE DS1104)
Fuzzy + ACO [160]	BLDC Mo- tor	Parallel Adap- tive	Medium	Improved response to load variation	Simulation only
Fuzzy SMC + PSO [161]	PMSM	Parallel	Medium- High	Improved speed regulation	Simulation only
Fuzzy + BCO [162]	Mobile Robot	Parallel Adap- tive	High	Improved fuzzy rule tuning	Simulation only
Fuzzy + Sand Cat Swarm + LQR [163]	BLDC Mo- tor	Cascaded	Medium	Reduced overshoot and faster settling time	Simulation only
Fuzzy + GA [164]	Induction Motor	Parallel	Medium	Improved effi- ciency	Simulation only
Fuzzy T-S + Whale Opti- mization [165]	BLDC Mo- tor	Cascaded	High	Enhanced tran- sient response	Simulation only
BWO + Vari- able Universe Fuzzy [166]	Electric Tractor (BLDC)	Parallel Adap- tive	Medium- High	Ripple reduction and faster regula- tion	Sim. + Observer-based
Fuzzy + GWO [167]	DC Motor	Parallel	Medium	Optimized fuzzy membership logic	FPGA Hard- ware
Fuzzy + Ant Lion Optimiza- tion [168]	SRM	Parallel Adap- tive	Medium	Enhanced tracking and torque control	Simulation only
Fuzzy FOPI + PSO (Proposed method)	BLDC Mo- tor	Parallel Adap- tive	Medium	Reduced over- shoot, torque ripple, fast dy- namic response	Sim. + HIL + Real Test (dSPACE CLP1104)

As observed from Table 5.6, the majority of existing studies are limited to simulation-level validation. Only two studies incorporate real-time testing, and among them, this work is the first one that combines simulation, HIL, and real-world test bench validation.

In terms of architecture, most methods employ parallel or adaptive fuzzy structures with medium computational complexity. However, none integrates a fully adaptive fuzzy–metaheuristic structure with a fractional-order PI controller. Therefore, this contribution is unique in three key aspects:

- It introduces a hybrid controller that combines adaptive fuzzy logic with online PSO

tuning to adjust all control parameters in real time.

- It incorporates a fractional-order control structure, offering improved tuning flexibility and robustness compared to conventional PI controllers.
- It provides a comprehensive validation through simulation, hardware-in-the-loop (HIL via dSPACE 1104), and real electric vehicle drive testing under realistic scenarios such as the NEDC and external load disturbances.

This comparative analysis highlights the novelty and practical applicability of the proposed A-HFOPI controller within the field of intelligent motor control.

5.6 Conclusion

This chapter reported the experimental validation and comparative assessment of the proposed energy-management and traction-control strategies for electric vehicle applications. Two complementary experimental platforms were employed: a HIL configuration based on dual dSPACE CLP1104 units and a real-time BLDC drive test bench. Together, these setups enabled a progressive transition from simulation to real hardware, while preserving controllability, repeatability, and measurement accuracy.

On the power-source side, an Energy Management System (EMS) was evaluated for a hybrid energy storage system combining a lithium-ion battery pack and a supercapacitor module. Although not the central contribution of this work, these simulations confirmed that a simple rule-based EMS can effectively separate the roles of the two devices: the battery supplies the average traction demand, whereas the supercapacitor handles fast current transients. Under a 140 s current profile emulating the traction system, the battery operated within a conservative depth-of-discharge range and the DC bus voltage was maintained close to 120 V, indicating that the proposed HESS configuration can deliver a DC-link quality compatible with the requirements of the traction system.

The main focus of the chapter was the traction system, controlled by a family of fractional-order PI (FOPI) regulators tuned using different metaheuristic algorithms (PSO, BCO, GWO) and by the proposed Adaptive Hybrid FOPI (A-HFOPI) controller. Simulation results first showed that the A-HFOPI strategy, which combines fuzzy logic with online PSO-based adaptation of K_p , K_i , and λ , yields the fastest convergence, the smallest overshoot, and the lowest error indices under step changes in reference speed and load torque disturbances. The subsequent HIL tests confirmed these trends under real-time constraints, demonstrating that

the controller maintains robustness when implemented on embedded hardware and interfaced with a high-fidelity plant model.

Real-time experiments on the laboratory BLDC drive further validated the practical applicability of the proposed control approach. Under acceleration tests, externally applied load torques, and a reduced NEDC profile, the A-HFOPI controller consistently provided improved tracking accuracy and shorter recovery times compared with both the conventional PI and the fixed-parameter FOPI controllers. In particular, it achieved a favourable compromise between speed regulation and electromagnetic torque quality, maintaining torque ripple at levels comparable to the PI controller while significantly enhancing dynamic response and long-term performance indices.

Overall, this chapter has demonstrated that the integration of an adaptive fuzzy-PSO fractional-order controller with a well-dimensioned DC-link supply leads to a high-performance traction system suitable for realistic EV operating scenarios. The combined use of simulation, HIL, and real-time experimentation provides a strong validation hierarchy for the proposed approach.

Building on these results, the next chapter 6 will address flux-regulation strategies aimed at further reducing power losses and improving the energetic efficiency of the BLDC drive. This subsequent analysis is intended to complement the speed-control improvements achieved here, contributing to a more comprehensive optimization of the EV traction system in terms of both dynamic performance and energy consumption.

Chapter 6

Flux Control for Power Losses Minimization

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6.1 Introduction

In the previous chapters, the hybrid electric vehicle powertrain was modelled and a coordinated control framework was developed to manage both the traction system and the hybrid energy storage composed of a lead–acid battery pack and a supercapacitor module. The energy management system (EMS) ensured an appropriate power sharing between the two sources, while advanced speed controllers based on fractional-order and fuzzy–metaheuristic techniques improved the dynamic performance of the BLDC traction motor under demanding driving conditions. Although these strategies enhanced torque tracking, speed regulation, and source utilization, the internal electrical losses in the traction motor remain a major factor limiting the overall efficiency, driving range, and lifetime of the battery–supercapacitor pack.

Conventional Direct Torque Control (DTC) schemes typically operate with a fixed stator flux reference chosen for worst-case torque requirements. Under partial load or moderate speed conditions, this fixed-flux operation leads to unnecessary copper and core losses, causing the motor to draw more power from the DC bus than strictly required. In the context of an EV powertrain supplied by a hybrid energy storage system, such excess losses translate into higher current stress, deeper cycling of the battery, and accelerated ageing of both the battery and the supercapacitor. Therefore, beyond improving torque and speed control, it is essential to act directly on the stator flux level to reduce losses and, consequently, extend the autonomy and service life of the onboard energy sources.

This chapter presents a second contribution focused on adaptive flux control for power loss minimization in the BLDC traction drive. The objective is to dynamically adjust the stator flux reference according to the instantaneous operating conditions, so that the motor operates closer to an energy-optimal point over a wide range of speeds and load torques. By reducing copper and core losses at the machine level, the demanded input power from the DC bus is lowered, which alleviates the energy drawn from the battery–supercapacitor pack and contributes to improved global efficiency of the EV powertrain.

Two complementary adaptive flux control strategies are proposed and integrated into the DTC framework. The first strategy is based on the Incremental Conductance (IncCond) principle, originally used in photovoltaic maximum power point tracking. In this context, the IncCond algorithm exploits the relationship between the electromagnetic power and the stator flux to estimate a power–flux gradient and iteratively adjust the flux reference toward a point where the power with respect to flux becomes optimal. The second strategy adopts a fuzzy-logic approach, where the stator flux reference is modified according to a rule base

driven by the motor speed and load torque. The fuzzy controller assigns low, medium, or high flux levels in real time, with the rule base designed to provide high flux for high-torque and low-speed operation, and reduced flux for light-load or high-speed conditions to minimize losses.

Both strategies are embedded within the same DTC architecture used for traction control, sharing the existing estimation blocks and hysteresis regulators, and are validated under a comprehensive set of operating scenarios using a Hardware-in-the-Loop (HIL) setup. The remainder of this chapter is organized as follows: Section 6.2 details the proposed adaptive flux control techniques based on Incremental Conductance and fuzzy logic. Section 6.3 presents the power calculation framework and the loss models used for evaluation. Section 6.4 reports and discusses the experimental validation results, including a comparative analysis with related works. Finally, Section 6.5 summarizes the main findings and highlights the contribution of adaptive flux control to the overall performance of the EV powertrain.

6.2 Adaptive Flux Control Techniques

Adaptive flux control represents a paradigm shift from traditional fixed-flux motor control strategies by enabling real-time adjustment of the stator flux reference in response to varying operating conditions [169]. Unlike conventional methods that maintain a constant flux regardless of load or speed changes, adaptive control dynamically adjusts the flux magnitude to minimize power losses while preserving torque performance [170]. This methodology leverages the fundamental observation that optimal flux levels are not fixed, but rather depend on the motor's instantaneous operating point, allowing for improved efficiency across a broad range of speed–torque combinations [171].

The theoretical foundation of this approach lies in the relationship between electromagnetic losses and flux magnitude: copper losses scale with the square of the current, whereas core losses are strongly influenced by flux density. By intelligently adapting the stator flux, both types of losses can be reduced simultaneously. This is particularly advantageous in applications with frequent variations in speed and load, such as electric vehicles and renewable-energy-based drives, where efficiency directly impacts autonomy and the lifetime of the energy sources.

In the following subsections, two adaptive flux control strategies are considered. The first is the Incremental Conductance (IncCond) method, which relies on power–flux characteristics to determine operating points associated with improved efficiency. The second is a Fuzzy-Logic-based controller that adapts the flux reference using a rule-based inference system

driven by real-time motor speed and load torque. Within the proposed framework, fuzzy logic is introduced as a key solution for minimizing power losses and enhancing the overall behaviour of the BLDC drive, while the IncCond strategy provides a complementary adaptive mechanism that further supports this objective.

6.2.1 Adaptive Flux Control via the Incremental Conductance

The Incremental Conductance (IncCond) method is utilized primarily for Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems, as in the literature [172–174], rather than for direct flux control in motors. The algorithm appears to adapt to the IncCond approach for flux control in electric motors, which is not a standard application.

In traditional applications, flux control in motors, especially Permanent Magnet Synchronous Motors (PMSMs), is often achieved through methods such as flux-weakening control. For example, a study by [175] presented a voltage-based flux-weakening strategy using a variable incremental controller to manage the flux component current in PMSMs.

The Incremental Conductance (IncCond) method is employed in this work for adaptive flux control of the BLDC motor, aiming to optimize the electromagnetic performance while maintaining stability under varying operating conditions. The Incremental Conductance method leverages the instantaneous relationship between power and flux to achieve faster convergence and reduced oscillations.

The proposed algorithm dynamically adjusts the flux reference on the basis of the incremental change in flux ($\Delta\phi$) and power (ΔP_{em}). The slope $\frac{\Delta P_{em}}{\Delta\phi}$ is computed, and its sign is used to adjust the flux:

$$\phi_{\text{ref}}(k+1) = \begin{cases} \phi_{\text{ref}}(k) + \Delta\phi, & \text{if } \frac{\Delta P_{em}}{\Delta\phi} > 0 \\ \phi_{\text{ref}}(k) - \Delta\phi, & \text{if } \frac{\Delta P_{em}}{\Delta\phi} < 0 \\ \phi_{\text{ref}}(k), & \text{if } \frac{\Delta P_{em}}{\Delta\phi} = 0 \end{cases} \quad (6.1)$$

This iterative process ensures that the flux converges to the point where $\frac{\partial P_{em}}{\partial\phi} = 0$, corresponding to the maximum power point.

To maintain system stability and prevent excessive adjustments, the flux reference is limited within a predefined range:

$$\phi_{\text{ref}} = \min(\max(\phi_{\text{ref}}, \phi_{\text{min}}), \phi_{\text{max}}) \quad (6.2)$$

where ϕ_{min} and ϕ_{max} are the lower and upper bounds of the flux, typically set as a percentage of the nominal flux.

Algorithm 1. Incremental Conductance Adaptation Algorithm Steps**1. Input and Output Definitions:**

- Inputs:
 - Instantaneous stator voltages: e_α, e_β
 - Instantaneous stator currents: i_α, i_β
 - Estimated stator flux: ϕ_s
 - Rotor speed: ω
- Output:
 - Adjusted flux reference: ϕ_{ref}

2. Initialization:

- Define nominal optimal flux ϕ_{opt}
- Set flux bounds: $\phi_{\text{min}}, \phi_{\text{max}}$
- Initialize flux reference: $\phi_{\text{ref}}(0)$
- Set previous flux reference: $\phi_{\text{ref, old}} \leftarrow \phi_{\text{ref}}(0)$
- Set previous power: $P_{\text{em, old}} \leftarrow 0$
- Define thresholds: $d_{\text{large}}, d_{\text{medium}}$
- Define step sizes: $\Lambda_{\text{large}}, \Lambda_{\text{medium}}, \Lambda_{\text{small}}$

3. Electromagnetic Power Calculation:

$$P_{\text{em}} = e_\alpha i_\alpha + e_\beta i_\beta \quad (6.3)$$

4. Flux Change Computation:

$$\Delta\phi = \phi_{\text{ref}} - \phi_{\text{ref, old}} \quad (6.4)$$

5. Power-Flux Gradient Estimation:

- If $\Delta\phi \neq 0$:

$$\text{gradient} = \frac{P_{\text{em}} - P_{\text{em, old}}}{\Delta\phi} \quad (6.5)$$

- Else:

$$\text{gradient} = 0 \quad (6.6)$$

6. Distance Calculation:

$$d = |\phi_{\text{ref}} - \phi_{\text{opt}}| \quad (6.7)$$

7. Adaptive Step Size Selection:

- If $d > d_{\text{large}}$: $\Lambda = \Lambda_{\text{large}}$
- Else if $d > d_{\text{medium}}$: $\Lambda = \Lambda_{\text{medium}}$
- Else: $\Lambda = \Lambda_{\text{small}}$

8. Flux Reference Adjustment:

- If gradient > 0 : $\phi_{\text{ref}} \leftarrow \phi_{\text{ref}} + \Lambda$
- If gradient < 0 : $\phi_{\text{ref}} \leftarrow \phi_{\text{ref}} - \Lambda$
- If gradient $= 0$: no change to ϕ_{ref}

9. Saturation Handling:

$$\phi_{\text{ref}} \leftarrow \max(\phi_{\text{min}}, \min(\phi_{\text{max}}, \phi_{\text{ref}})) \quad (6.8)$$

10. Update State Variables:

- $P_{\text{em, old}} \leftarrow P_{\text{em}}$
- $\phi_{\text{ref, old}} \leftarrow \phi_{\text{ref}}$

6.2.2 System Integration and Control Architecture Via the Incremental Conductance

Figure 6.1 illustrates the complete control architecture for the proposed BLDC motor drive system, integrating adaptive flux regulation with multi-level control strategies to ensure dynamic performance, torque accuracy, and energy-efficient operation.

The control loop operates as follows:

1. **Measurement and Feedback Acquisition:** The system continuously measures the stator current components and rotor speed, via either sensors or sensorless estimation based on the back-EMF. These signals form the foundation of the real-time feedback loop.

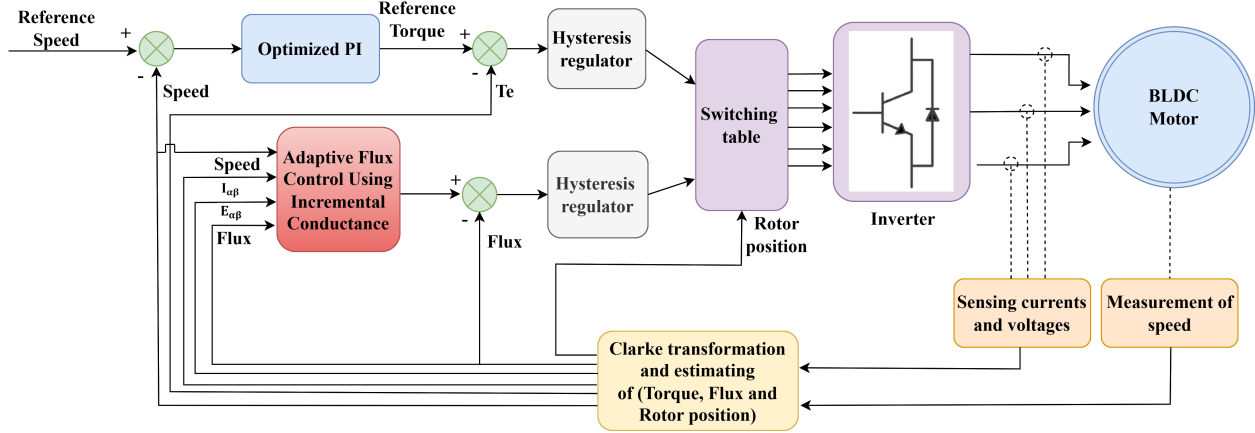


Figure 6.1: Control scheme integrating IncCond adaptive flux regulation into the DTC.

2. **Clarke Transformation and Estimation Block:** The acquired phase currents are transformed into the stationary $\alpha\beta$ reference frame. This enables the estimation of electromagnetic torque, stator flux magnitude, and rotor position—essential parameters for both control and observation tasks.
3. **Adaptive Flux Regulation via Incremental Conductance:** Leveraging the incremental conductance (IncCond) principle, the adaptive control module dynamically adjusts the reference flux. By analyzing the power contribution in the $\alpha\beta$ frame ($P_{em} = e_{\alpha}i_{\alpha} + e_{\beta}i_{\beta}$), the controller tunes the flux reference with adaptive step sizes to maintain optimal operating conditions across varying load and speed profiles.
4. **Speed and Torque Control using Optimized PI Loops:** A cascade control structure is adopted, where an outer-loop PI controller regulates speed and the inner-loop controller handles current (torque) control. The PI parameters are optimized to maintain closed-loop stability while incorporating the flux reference updates from the adaptive module.
5. **Hysteresis Current Regulation:** Two independent hysteresis regulators compare the measured and reference current components (i_{α} , i_{β}) and generate switching signals when deviations exceed a predefined threshold. This ensures a fast current response and reduced torque ripple.
6. **Switching Table Logic:** Based on the outputs from the hysteresis controllers, the switching table determines the appropriate gating signals for the inverter. The commutation strategy adheres to the six-step method, ensuring proper sector alignment with minimal switching losses.

7. **Inverter and Motor Actuation:** The inverter translates control signals into high-speed switching patterns, delivering the regulated voltage and current to the BLDC motor. This final actuation ensures precise torque production and effective utilization of the adaptive flux strategy.

This layered control structure successfully integrates adaptive flux regulation with conventional motor control techniques. The key benefits include the following:

- Real-time optimization of the stator flux using IncCond without requiring a detailed motor model.
- Enhanced dynamic response through fast hysteresis-based current regulation.
- Robust speed and torque tracking using cascade-structured PI controllers.
- Reliable switching logic supports efficient commutation under all operating conditions.

6.2.3 Adaptive Flux Control via the Fuzzy Logic

Fuzzy logic controllers (FLCs) are particularly well-suited for nonlinear systems such as electric drives, as they do not require an exact mathematical model and can incorporate heuristic rules derived from expert knowledge and experimental observations [17]. In this work, the fuzzy logic module adjusts the stator flux reference in real time based on two key inputs: the motor speed and load torque.

The rule base shown in Table 6.1 is constructed to ensure high flux at low speeds (for torque generation), medium flux at moderate conditions (for efficiency), and low flux at high speeds with low torque (to minimize core losses). Similar strategies have been reported in literature to improve DTC performance and extend battery life in electric vehicles [176, 177].

Table 6.1: Fuzzy logic rule table for adaptive flux control.

Speed \ Torque	Low	Medium	High
Low	High Flux	High Flux	High Flux
Medium	Medium Flux	Medium Flux	High Flux
High	Low Flux	Medium Flux	High Flux

In this work, the "Medium Flux" level corresponds to the nominal stator flux ϕ_n . The "Low" and "High" flux levels are set as approximately 70% and 130% of this nominal value, respectively, on the basis of empirical tuning for best performance.

Algorithm 2. Fuzzy Flux Adaptation Algorithm Steps

1. Input Acquisition:

- The instantaneous rotor speed ω and electromagnetic torque T_e are extracted from the control loop and provided as inputs to the fuzzy inference system.

2. Normalization and Fuzzification:

- The crisp inputs ω and T_e are first normalized by mapping them to a defined universe of discourse, typically scaled between 0 and 1, based on their expected minimum and maximum values.
- These normalized values are then converted into fuzzy linguistic variables (e.g., Low, Medium, High) using trapezoidal membership functions, as shown in Figure 6.4.

3. Rule Evaluation:

- The Mamdani inference engine evaluates the fuzzy rules as depicted in Table 6.1, to infer a suitable fuzzy output category for the flux reference (e.g., Low, Medium, High).

4. Defuzzification:

- The combined fuzzy output is transformed into a crisp stator flux reference ϕ^* using the center of gravity method.

5. Flux Update:

- The resulting flux reference ϕ^* is applied to the DTC block to influence the inverter switching decisions and motor behavior.

6.2.4 System Integration and Control Architecture via the Fuzzy Logic

The proposed fuzzy flux controller is integrated into the DTC framework as illustrated in Figure 6.2. The architecture operates as follows:

- Motor currents and speed are measured in real time and processed via Clarke transformation to estimate torque, flux, and rotor position.
- A PI speed controller (tuned offline using optimization algorithms) generates the torque reference.

- The fuzzy logic controller adaptively adjusts the flux reference λ^* based on real-time speed and torque estimation.
- Both flux and torque references are fed into hysteresis regulators that determine the optimal switching states.
- A switching table selects appropriate voltage vectors that control the inverter and drive the BLDC motor.

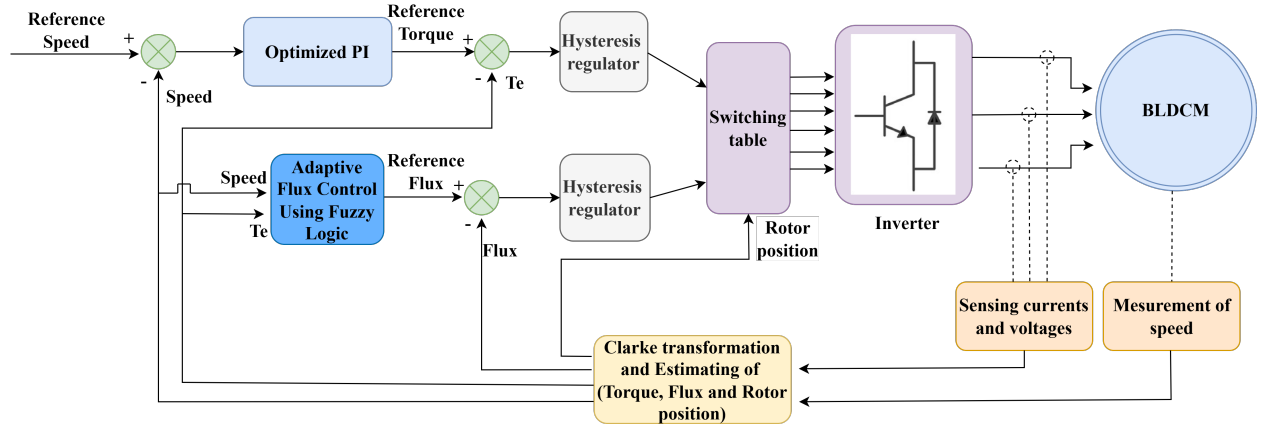


Figure 6.2: Control architecture integrating fuzzy-logic adaptive flux control into the DTC.

The internal structure of the fuzzy logic controller and the gain application block is shown in Figure 6.3. The controller takes speed and torque as inputs and outputs a scaling factor that adjusts the reference flux. A gain of 1.45 is applied to the output of the fuzzy logic controller to ensure that the resulting flux level remains within the desired operating band of 70% to 130% of the nominal value.

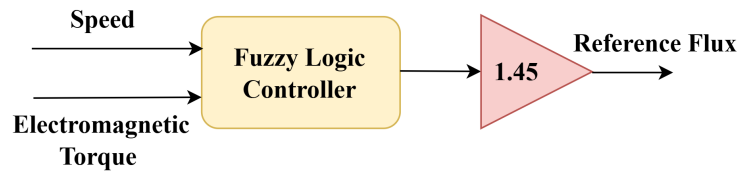


Figure 6.3: Fuzzy logic controller block and gain scaling for the reference flux.

The membership functions used for the fuzzification of the input (torque and speed) and output (flux) variables are depicted in Figure 6.4. Each variable is divided into three fuzzy subsets—Low, Medium, and High—using trapezoidal membership functions for simplicity and computational efficiency. The Mamdani fuzzy inference system is employed for the control strategy.

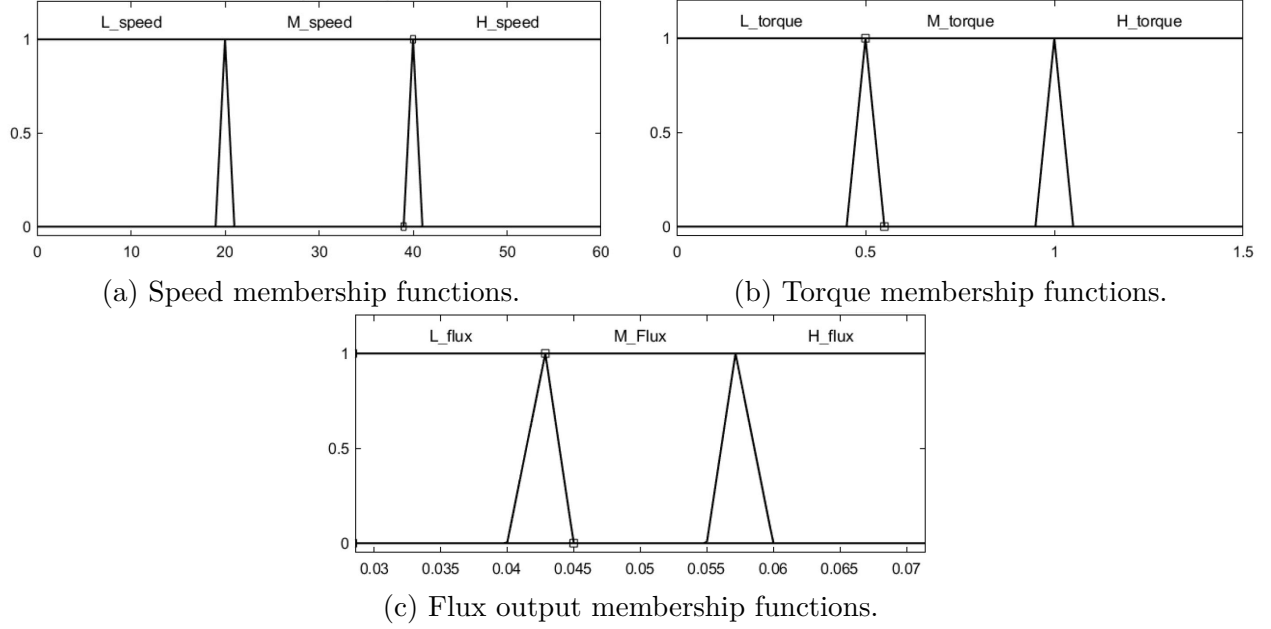


Figure 6.4: Fuzzy membership functions: (a) speed, (b) torque, and (c) output flux, using trapezoidal membership functions and the Mamdani fuzzy inference system.

This hybrid approach retains the simplicity and fast dynamic response of a classical DTC while improving the energy efficiency and reducing the torque ripple. Several studies have confirmed the benefits of integrating fuzzy control in electric vehicle drives [178, 179].

6.3 Power Calculation

This section outlines the methodology used to compute various forms of power and losses in the BLDC motor system. Accurate power calculations are essential for evaluating system efficiency and identifying loss contributors, enabling strategies for performance optimization.

6.3.1 Input Power

The total input power supplied to the system is calculated as:

$$P_{in} = V_{in} \cdot I_{in} \quad (6.9)$$

where:

- V_{in} is the DC bus voltage applied to the inverter,
- I_{in} is the total current drawn from the supply.

6.3.2 Electromagnetic Power

The electromagnetic (mechanical) power transferred from electrical to mechanical form is given by:

$$P_e = \omega \cdot T_{em} \quad (6.10)$$

where:

- ω is the electrical angular velocity (rad/s),
- T_{em} is the electromagnetic torque produced by the motor.

6.3.3 Core Losses

Core losses in magnetic materials mainly consist of hysteresis and eddy current losses. The total core loss is computed via the following empirical relation:

$$P_{core} = \Phi^2 \cdot (K_h \cdot N + K_e \cdot N^2) \quad (6.11)$$

where:

- Φ is the magnetic flux density (Wb/m²),
- K_h and K_e are material-dependent hysteresis and eddy current coefficients, respectively, obtained from datasheet characterization,
- N is the rotational speed of the rotor in rpm.

Hysteresis losses scale linearly with speed, whereas eddy current losses grow quadratically with speed. This implies that as N increases, eddy current losses dominate the total core loss contribution [180].

6.3.4 Copper Losses

Copper losses are resistive (Joule) losses due to current flow in motor windings. In a three-phase BLDC motor, these losses are expressed as:

$$P_{cu} = 3 \cdot R \cdot I^2 \quad (6.12)$$

where:

- R is the resistance of a single phase winding,

- I is the RMS value of the current in each phase.

Minimizing copper losses is crucial for enhancing motor efficiency. This can be achieved through:

- Using low-resistance materials (e.g., copper with high conductivity),
- Increasing conductor cross-sectional area to reduce resistance,
- Optimizing current levels based on load conditions.

6.3.5 Total Power Losses

The total losses in the motor system are the sum of the copper and core losses:

$$P_{\text{tot}} = P_{\text{cu}} + P_{\text{core}} \quad (6.13)$$

This total power loss directly influences system efficiency, which is calculated as:

$$\eta = \frac{P_e}{P_{\text{in}}} \times 100\% \quad (6.14)$$

By incorporating adaptive flux control strategies as illustrated above, both P_{cu} and P_{core} can be minimized, leading to improved overall drive efficiency.

6.4 Experimental Validation and Discussion

Using the HIL test bench setup illustrated previously in Figure 5.4, combined with the DTC scheme and the switching strategy detailed in Table 6.2, in the proposed setup, MONITOR 1 runs the control loop and receives key feedback signals from the simulated plant through analog channels. Specifically, ADC1 reads the rotor position, ADC2 captures the torque, ADC3 receives the flux value, and ADC5 monitors the rotor speed, while the PWM control signals generated by the controller are transmitted via the slave I/O interface to drive the inverter gates connected to the plant side. Meanwhile, MONITOR 2 emulates the plant (power system) dynamics; it receives the inverter gate signals via its I/O interface and generates the corresponding analog outputs. These outputs are then transmitted back to the controller side through DAC channels: DAC3 carries the rotor position signal, DAC4 transmits the torque, DAC6 represents the flux, and DAC8 contains the rotor speed. This closed-loop signal exchange replicates the real-time behavior of the BLDC motor system with high fidelity. This section presents a comparative analysis between the traditional fixed flux reference (set to

the nominal value) and the two proposed adaptive flux strategies: Incremental Conductance (IncCond) and Fuzzy Logic control.

Table 6.2: Switching table used in the DTC scheme.

Case n°	S_a	S_b	S_c
1	0	0	1
2	0	1	0
3	0	1	1
4	1	0	0
5	1	0	1
6	1	1	0

The evaluation is structured to capture motor performance under a comprehensive set of twelve operating conditions. These conditions are grouped based on torque levels over a 24-second duration, as follows:

- **0–6 s:** Zero Load Torque across Low, Medium, and High Speeds
- **6–12 s:** Low Load Torque across Low, Medium, and High Speeds
- **12–18 s:** Medium Load Torque across Low, Medium, and High Speeds
- **18–24 s:** High Load Torque across Low, Medium, and High Speeds

The torque load values applied during the experimental validation are as follows:

- **Low Torque** = 0.4 N.m
- **Medium Torque** = 0.8 N.m
- **High Torque** = 1.2 N.m

Each condition lasts 2 s, resulting in 12 sub-scenarios. This duration was selected to ensure that both transient and steady-state behavior could be captured for each condition, allowing for accurate comparisons across control strategies. The complete scenario matrix is summarized in Table 6.3, and the torque load profile is illustrated in Figure 6.5. The PI controller used in the speed regulation loop was carefully tuned through offline optimization to ensure a fast dynamic response and minimal steady-state error, and then integrated into the overall system architecture, as shown in Figure 6.1 and Figure 6.2. To ensure clarity, the speed levels are defined as follows: *low speed* refers to the range $[0, 20[$ rad/s, *medium speed* to $[20, 40[$ rad/s, and *high speed* to $[40, 60]$ rad/s. It is important to note that the transitions in speed and torque were not applied simultaneously; to ensure system stability

and avoid overlapping transients, each speed adjustment was introduced approximately 0.1 s before the corresponding torque change. This configuration ensured a stable response and enabled accurate evaluation of each operating point. The BLDC motor parameters used in the validation are provided in Table 6.4.

Table 6.3: Speed and torque load combinations for experimental validation.

Time Interval (s)	Speed Level	Torque Load
[0, 2]	Low	Zero
[2, 4]	Medium	Zero
[4, 6]	High	Zero
[6, 8]	Low	Low
[8, 10]	Low	Medium
[10, 12]	Low	High
[12, 14]	Medium	Low
[14, 16]	Medium	Medium
[16, 18]	Medium	High
[18, 20]	High	Low
[20, 22]	High	Medium
[22, 24]	High	High

Table 6.4: BLDC motor parameters.

Parameter	Value	Unit
Electric power P_{elec}	100	W
Maximum speed ω	60	rad/s
Maximum torque T_L	1.5	Nm
Stator resistance R_s	0.18	Ω
Nominal flux ϕ_n	0.07145	Wb
Stator phase inductance L_s	8.5e-3	H
Number of pole pairs p	4	-
Moment of inertia J	0.00062	kg · m ²
Damping coefficient B	0.0003035	Ns/m
Rated voltage V_{dc}	48	V
Hysteresis constant K_h	0.05	-
Eddy current constant K_{eddy}	0.001	-

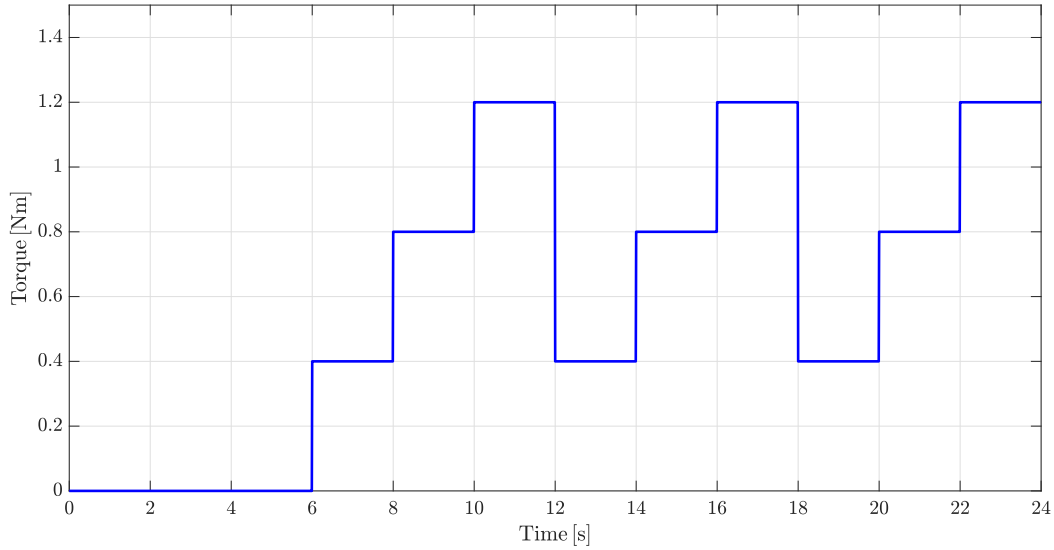


Figure 6.5: Load torque profile.

6.4.1 Results

In this section, the experimental results are presented, focusing on the performance of the proposed adaptive flux strategies (Incremental Conductance and Fuzzy Logic) compared with the traditional fixed flux strategy. The results are illustrated through various figures that present the system's behavior under different operating conditions.

The waveforms for the stator current and back-EMF are shown in Figures 6.6 and 6.7, respectively. These figures provide insights into the motor's behavior, where the stator current follows a sinusoidal pattern for the fixed flux control strategy and the back-EMF exhibits a typical trapezoidal waveform.

Figure 6.8 compares the speed performance for the different flux control strategies, demonstrating how the motor responds to changes in load and speed under each strategy.

The torque comparison for each flux control strategy is shown in Figure 6.9, highlighting the differences in electromagnetic torque behavior between the fixed flux, incremental conductance, and fuzzy logic strategies.

Flux behavior comparisons for the three strategies are provided in Figure 6.10, where the adaptive flux strategies dynamically adjust the flux, while the fixed flux strategy maintains a constant value.

Figures 6.11, 6.12, 6.13 and 6.14 present grouped comparisons of power metrics across all strategies, including input power, electromagnetic power, core losses, and copper losses. These plots are segmented per strategy to visually emphasize the impact of flux adaptation.

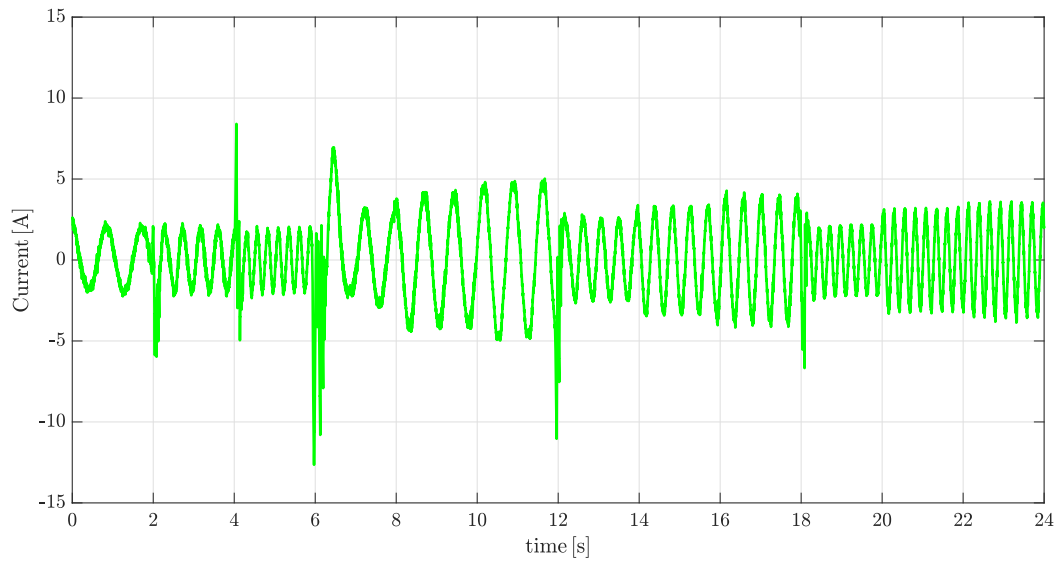


Figure 6.6: Stator current waveform under fixed flux control.

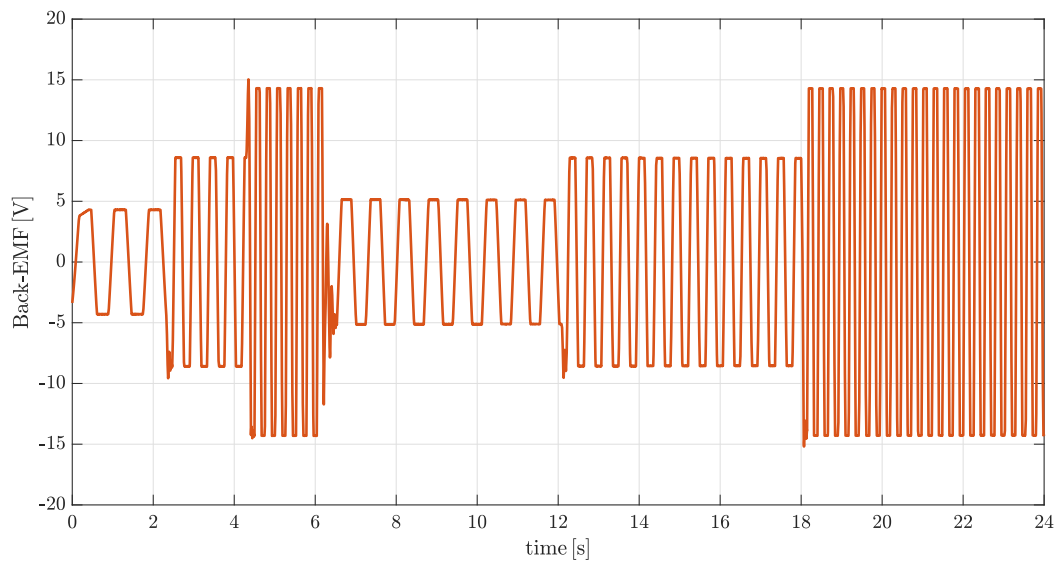


Figure 6.7: Back-EMF waveform under fixed flux control.

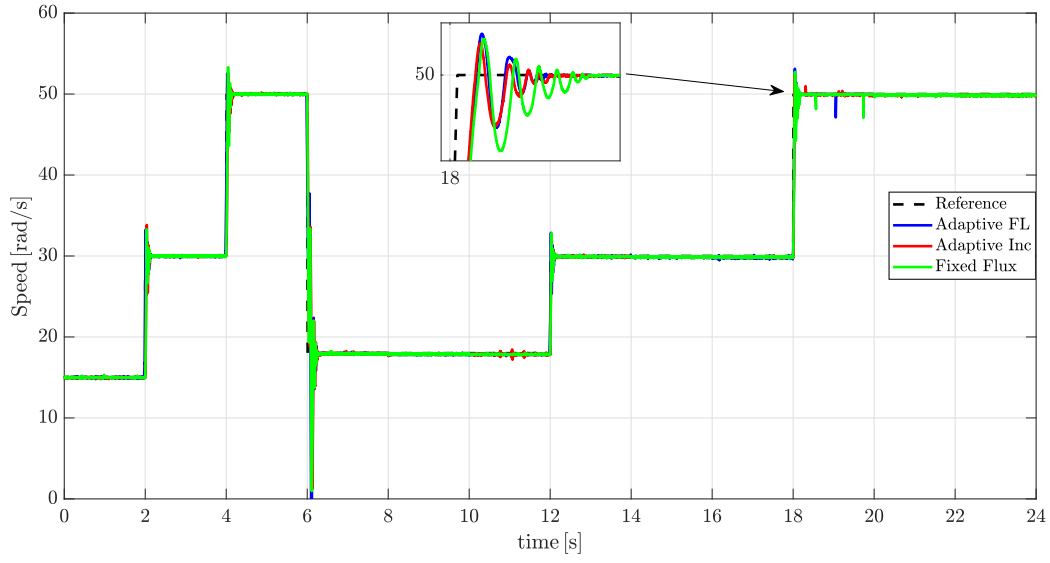


Figure 6.8: Speed performance comparison for fixed flux, incremental conductance, and fuzzy logic flux control strategies.

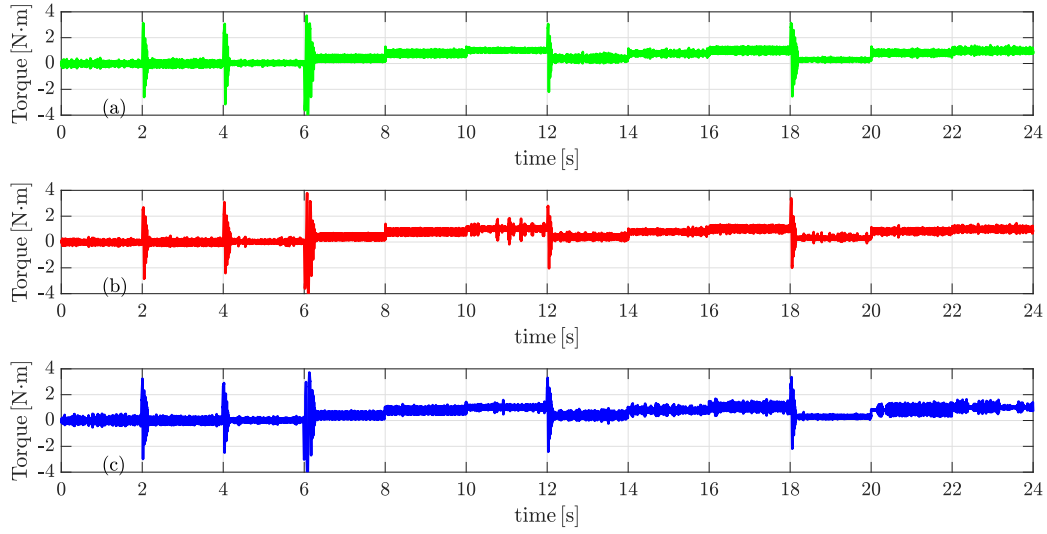


Figure 6.9: Electromagnetic torque comparison for different flux control strategies: (a) Fixed Flux; (b) Incremental Conductance and (c) Fuzzy Logic.

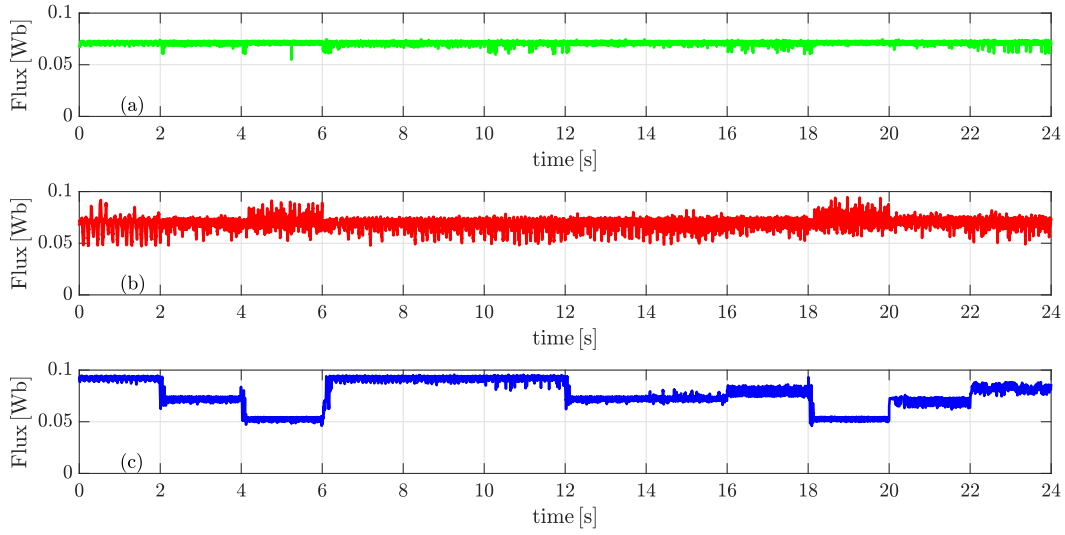


Figure 6.10: Flux behavior comparison for different flux control strategies: (a) Fixed Flux; (b) Incremental Conductance and (c) Fuzzy Logic.

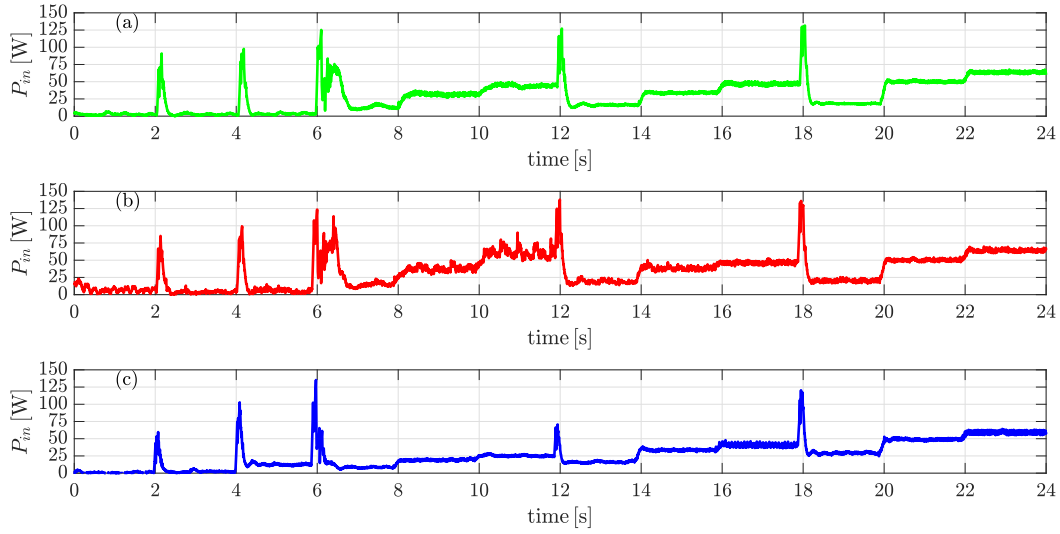


Figure 6.11: Input power comparison for different flux control strategies: (a) Fixed Flux; (b) Incremental Conductance and (c) Fuzzy Logic.

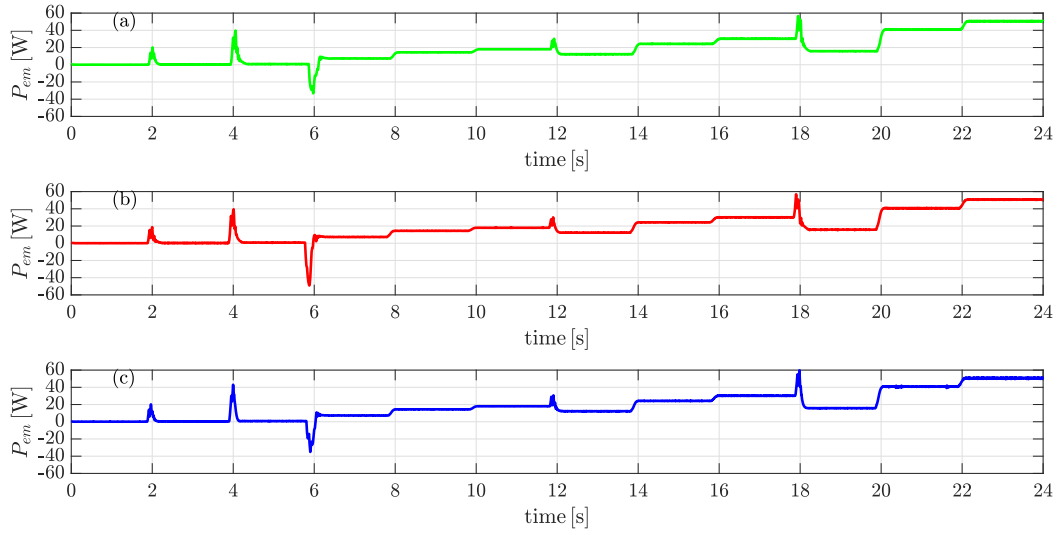


Figure 6.12: Electromagnetic power comparison for different flux control strategies: (a) Fixed Flux; (b) Incremental Conductance and (c) Fuzzy Logic.

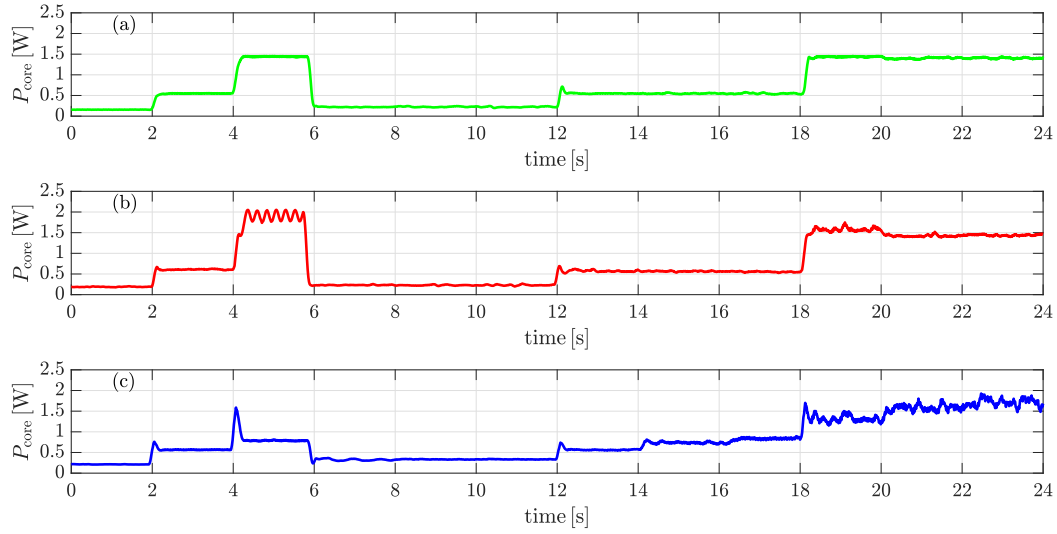


Figure 6.13: Core losses comparison for different flux control strategies: (a) Fixed Flux; (b) Incremental Conductance and (c) Fuzzy Logic.

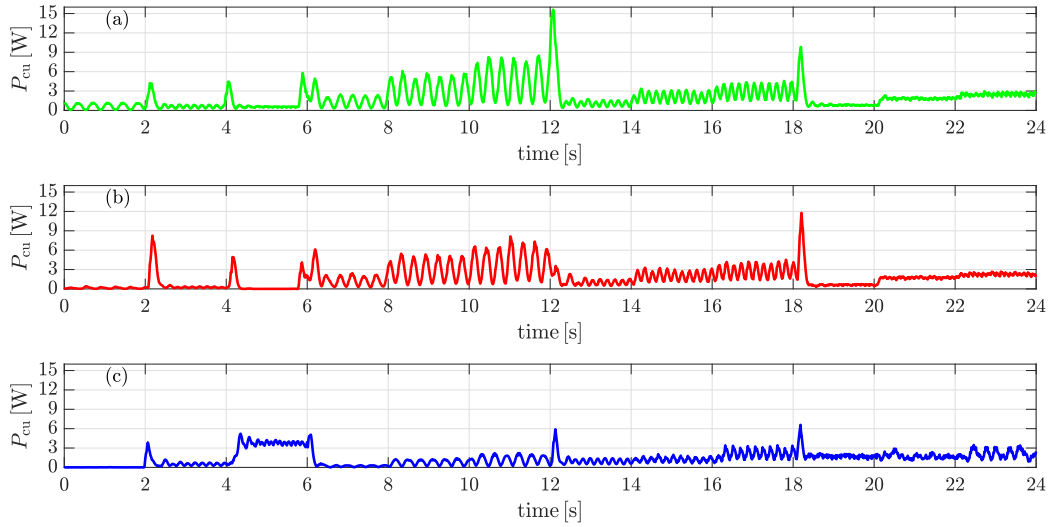


Figure 6.14: Copper losses comparison for different flux control strategies: (a) Fixed Flux; (b) Incremental Conductance and (c) Fuzzy Logic.

6.4.2 Discussion

The numerical results of average power values for each method are summarized in Table 6.5. These values were computed as mean values over 24 seconds, which is the standard approach in power system efficiency analysis. This average-based evaluation reflects the long-term electrical stress on the motor [17].

Table 6.5: Mean power calculations and efficiency comparison.

Metric	Fixed Flux	IncCond Method	Fuzzy Logic
Flux Range (Wb)	0.07145	Adaptive	Adaptive
Input Power (W)	34.15	31.21	26.55
Electromagnetic Power (W)	16.78	16.45	17.68
Core Losses (W)	0.71	0.70	0.66
Copper Losses (W)	2.03	1.76	1.38
Total Power Losses (W)	2.74	2.46	2.04
System Efficiency (%)	49.13	52.70	66.59
Loss Reduction vs Fixed Flux (%)	—	10.22	25.55

Among the three strategies, Fuzzy Logic exhibits the best overall performance. It achieves the lowest input power consumption at 26.55 W, while delivering the highest electromagnetic power at 17.68 W. In addition, it significantly reduces copper losses to 1.38 W and core losses to 0.66 W, both of which are the lowest among all methods. This results in the lowest total power losses, amounting to 2.04 W, and leads to a system efficiency of 66.59%—the highest observed. The IncCond method offers intermediate performance, with an input power of

31.21 W, electromagnetic power of 16.45 W, core losses of 0.70 W, and copper losses of 1.76 W. Its total power losses are reduced to 2.46 W, corresponding to a 10.22% loss reduction compared to the fixed flux approach. The system efficiency achieved is 52.70%. In contrast, the fixed flux strategy results in the highest energy losses and the lowest system efficiency, with an input power of 34.15 W, total power losses of 2.74 W, and an overall efficiency of 49.13%. These results validate the effectiveness of adaptive flux control—particularly Fuzzy Logic—in minimizing power losses and enhancing overall drive efficiency. The bar charts in Figure 6.15 present a visual summary of the performance metrics listed in Table 6.5, highlighting efficiency, input power, total losses, and copper losses for the fixed flux, incremental conductance, and fuzzy logic strategies.

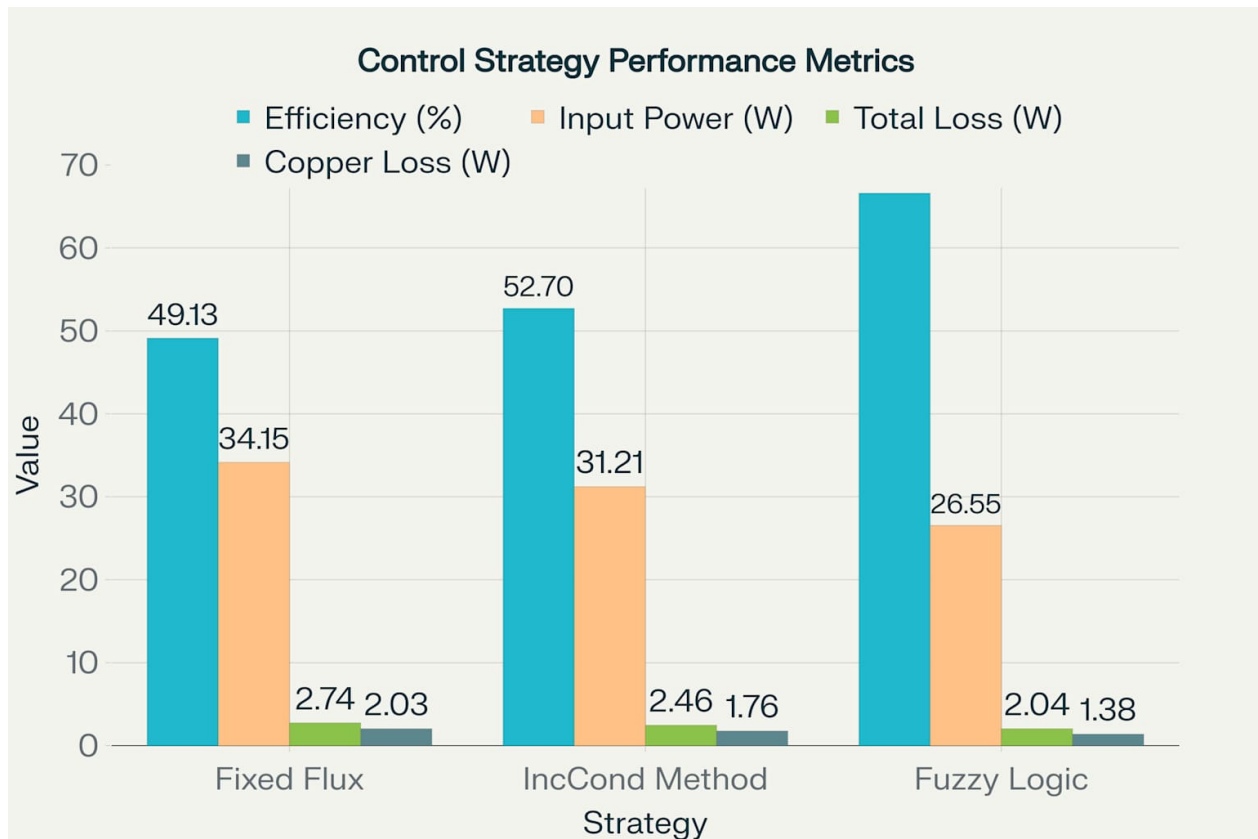


Figure 6.15: Control strategy performance metrics: efficiency, input power, total and copper losses for Fixed Flux, Incremental Conductance, and Fuzzy Logic approaches.

The experimental results clearly validate the effectiveness of adaptive flux control strategies in minimizing power losses and enhancing the overall efficiency of BLDC motor drives. Among the three evaluated methods, the Fuzzy Logic controller achieved the best overall performance, realizing a 25.55% reduction in total power losses and a system efficiency of 66.59%. The Incremental Conductance approach also demonstrated significant benefits,

yielding a 10.22% loss reduction compared to the fixed flux baseline. These improvements were achieved through intelligent real-time flux regulation: the IncCond method provided fast and responsive flux adaptation based on power–flux gradient analysis, while the fuzzy controller fine-tuned the flux reference using a rule-based system informed by motor speed and load torque.

All strategies were implemented and validated using HIL environment based on a dual dSPACE 1104 card setup. The control algorithm was executed in real time using a DTC scheme, where accurate flux estimation was enabled by leveraging the known internal parameters of the BLDC motor. The real-time simulation model of the motor included detailed modeling of electromagnetic dynamics, core losses, and switching behavior, ensuring high-fidelity interaction between hardware and simulation domains. The use of a small-scale 100 W BLDC motor, with fully characterized internal parameters, allowed precise analysis of efficiency trends and loss mechanisms across a wide range of operating points.

The proposed framework, integrating IncCond and fuzzy logic within a real-time DTC control architecture, demonstrates a practical, scalable, and energy-efficient solution for intelligent motor drives. It successfully bridges advanced control theory and embedded implementation, offering a concrete pathway toward optimized flux control in energy-sensitive applications. The demonstrated loss minimization, control responsiveness, and implementation feasibility collectively represent a meaningful contribution to the advancement of BLDC motor drive.

6.4.3 Comparative Analysis with Related Works

To highlight the effectiveness of the proposed adaptive flux control strategies, Table 6.6 provides a comparison with relevant studies focused on minimizing power losses in BLDC motor drives using various advanced control techniques. The table summarizes the control strategy, validation method, reported loss reduction, and key implementation notes.

Table 6.6: Comparison of different control strategies for power loss minimization in BLDC motor drives.

Control Method	Strategy	Validation	Loss Reduction	Control Highlights
Fuzzy PWM [181]	Rule-based PWM Fuzzy Control	Simulation only	14.2%	Reduced switching losses through waveform shaping based on fuzzy rules.
D-axis Current Control [182]	Sensorless D-axis Flux Regulation	Experimental	11.7%	Real-time torque improvement via d-axis current decoupling and loss suppression.
Predictive Flux Control [183]	Model-Predictive Flux Optimization	Simulation and Experimental	16.4%	Efficiency improved through predictive flux regulation and feedback-based control.
Adaptive PI [184]	Optimal PI Control using Adaptive Algorithm	Simulation only	18.6%	Real-time tuning of PI parameters to reduce resistive losses.
Harmonic Minimization [185]	Optimized Harmonic-Based Switching	Experimental	20.3%	Loss mitigation through harmonic distortion minimization and ripple control.
MTPA-Pseudo FOC [186]	Maximum Torque/Power with Pseudo FOC	Experimental	23.1%	Improved torque per ampere and copper loss reduction using enhanced FOC.
IncCond (This Work)	Incremental Conductance Flux Control	Hardware-in-the-Loop	10.22%	Fast and responsive flux adaptation based on power-flux gradient analysis.
Fuzzy Logic (This Work)	Adaptive Rule-Based Fuzzy Control	Hardware-in-the-Loop	25.55%	Rule-based adaptation using speed and torque inputs with real-time implementation.

As summarized in Table 6.6, the proposed fuzzy logic-based adaptive flux controller achieves the highest loss reduction of 25.55%, outperforming other advanced strategies such as MTPA with pseudo-FOC (23.1%), harmonic-based switching (20.3%), and adaptive PI control (18.6%). While these methods improve efficiency through techniques like optimized torque utilization, harmonic suppression, or adaptive gain tuning, they do not directly implement real-time adaptive flux control. In contrast, the fuzzy logic and incremental conductance strategies presented in this work are the only approaches in the comparison that explicitly regulate the flux reference for BLDC motor drives based on instantaneous speed and torque conditions. This distinction underscores the practical relevance and effectiveness of adaptive flux control in reducing copper and core losses under dynamic operating conditions, as demonstrated

through HIL-based validation.

6.5 Conclusion

This chapter addressed the second main contribution of this work, namely the reduction of power losses in the electric vehicle powertrain through adaptive flux control of the BLDC traction motor. Whereas the previous chapter focused on energy management and advanced speed regulation using a hybrid fuzzy–PSO fractional-order PI strategy, the present chapter concentrated on the internal loss mechanisms of the machine itself and examined how dynamic flux regulation can reduce the electrical energy requested from the hybrid storage system composed of a lithium-ion battery and a supercapacitor.

Two complementary adaptive flux control strategies were formulated and integrated into a DTC-based drive: an Incremental Conductance (IncCond) method and a fuzzy-logic flux controller. The IncCond approach adjusted the stator flux reference on the basis of the instantaneous power–flux gradient, steering the operating point toward a region of reduced losses without requiring an explicit loss model. The fuzzy-logic controller, in turn, adapted the flux level according to real-time estimates of speed and electromagnetic torque, embedding expert knowledge into a compact rule base that assigns low, medium, or high flux levels depending on the operating condition.

Both strategies were implemented and evaluated in a Hardware-in-the-Loop environment built around a dual dSPACE 1104 setup and a detailed BLDC motor model including copper and core losses. The comparative analysis with a conventional fixed-flux reference showed that adaptive flux regulation effectively decreases total power losses and improves drive efficiency, while preserving an adequate electromagnetic power level and acceptable torque quality. The fuzzy-logic approach provided the most favourable compromise between loss reduction, control simplicity, and robustness, whereas the Incremental Conductance method confirmed the feasibility of gradient-based flux adaptation in real time.

From the perspective of the global EV powertrain, these results confirm that adaptive flux control is an effective lever for reducing the electrical energy drawn from the battery–supercapacitor hybrid storage system for a given driving profile. By lowering the average input power at the DC bus and mitigating internal machine losses, the proposed strategies contribute to extending the vehicle autonomy and alleviating the ageing of the storage components. In combination with the energy management and adaptive speed-control schemes developed in the previous chapter, the flux-control techniques presented here form a coherent and complementary set of tools for improving the overall energetic performance of electric

vehicle drive systems. The broader synthesis of these contributions within the global EV control framework is provided in the general conclusion of Chapter [7](#).

Chapter 7

General Conclusion

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7.1 Conclusion

This thesis has presented a comprehensive framework for the modeling, control, and optimization of hybrid electric vehicles (HEVs), combining advanced energy management and intelligent traction control strategies. By merging adaptive control, fractional-order theory, and metaheuristic optimization within a unified structure, the research has demonstrated substantial improvements in system efficiency, dynamic performance, and operational robustness. The developed methods provide practical solutions for real-world EV powertrains, where energy efficiency, responsiveness, and reliability are critical requirements.

The work began in the [first chapter](#) with a contextual overview of the evolution of electric vehicles, outlining major technological challenges—such as battery limitations, powertrain efficiency, and control complexity—and defining the objectives of this study. The analysis established the motivation for hybridized and adaptive control schemes capable of overcoming the inherent nonlinearities and energy constraints of EV systems.

The [second chapter](#) reviewed the state of the art in EV performance optimization, covering existing control topologies, energy management strategies, and advanced motor control techniques including Field-Oriented Control (FOC) and Direct Torque Control (DTC). The review also examined the growing role of artificial intelligence and optimization algorithms in achieving higher levels of system intelligence and autonomy.

In [chapter three](#), detailed mathematical models were developed for the core components of the hybrid electric powertrain—namely the lithium-ion battery, supercapacitor, DC–DC converters, and brushless DC (BLDC) motor. A state-space representation of the motor and a dynamic vehicle model were derived to enable precise simulation and controller design. This modeling framework established the analytical foundation for subsequent control and optimization studies.

The [fourth chapter](#) integrated energy management and traction control strategies into a single, coherent control architecture. On the power-source side, an Energy Management System (EMS) based on frequency separation and Lyapunov control was designed to regulate the DC bus voltage and optimally share power between the battery and supercapacitor. On the traction side, advanced speed regulation was achieved using a fractional-order PI (FOPI) controller, with performance enhanced through metaheuristic optimization (PSO, BCO, GWO). Building upon this foundation, a hybrid fuzzy–PSO self-tuning FOPI controller was developed to achieve online adaptivity, enabling dynamic gain and order adjustment under varying operating conditions. This controller successfully combined the interpretability of fuzzy logic with the global search capability of PSO, offering superior transient and steady-

state performance.

The experimental validation presented in [chapter five](#) confirmed the feasibility and robustness of the proposed strategies through Hardware-in-the-Loop (HIL) and real-time test-bench implementations. The results showed excellent agreement with simulation outcomes, demonstrating improved torque tracking, minimized speed overshoot, and enhanced energy utilization. The hybrid controller outperformed classical methods in terms of stability, adaptability, and computational efficiency.

Finally, [chapter six](#) introduced adaptive flux control techniques aimed at minimizing power losses in BLDC motor drives. Using fuzzy logic and the Incremental Conductance (IncCond) algorithm, the stator flux reference was continuously adjusted to match the instantaneous load and speed requirements. This resulted in significant reductions in copper and core losses, contributing to overall efficiency improvement and thermal stress mitigation.

In conclusion, the research presented in this thesis advances the state of electric vehicle control by bridging modeling precision, intelligent adaptation, and optimization-based tuning. The proposed hybrid Fuzzy–PSO fractional-order control and adaptive flux regulation strategies collectively improve energy efficiency, speed response, and fault tolerance, while reducing power losses and extending battery life. These contributions not only enhance the scientific understanding of intelligent control for EV systems but also provide practical frameworks for future industrial implementation and research extensions.

7.2 Future Work

To ensure the continued advancement of the research conducted in this thesis, future investigations can be directed toward exploring several promising directions that align with current developments in electric vehicle (EV) technologies and intelligent control systems. Potential areas of focus include the following:

- **Hardware Implementation of Fractional-Order Controllers:** While fractional-order controllers have demonstrated superior performance in simulation and hardware-in-the-loop testing, and implementing them efficiently in embedded real-time systems remains a challenge. Future research may explore low-complexity approximations and digital realization techniques for fractional operators using FPGAs, DSPs, or microcontrollers with limited computational resources.
- **Intelligent Fault Detection and Tolerant Control:** Extending the developed control framework to include intelligent fault detection, diagnosis, and reconfiguration

strategies can further increase system reliability. Future efforts could involve the use of machine learning or observer-based methods to detect sensor and actuator faults, enabling resilient performance even in degraded operating modes.

- **Integration with Battery Thermal Management Systems (BTMS):** As battery performance is strongly influenced by temperature, integrating the energy management strategy with thermal control systems could provide further improvements in battery lifespan, charging efficiency, and energy utilization. Research may investigate the co-optimization of energy and thermal flows via predictive or model-based control techniques.
- **Vehicle-to-Grid (V2G) and Bidirectional Energy Flow Optimization:** With the increasing adoption of smart grid technologies, future work can explore V2G integration strategies to enable EVs to function as energy storage units. Optimizing bidirectional energy flows while ensuring minimal battery degradation and grid stability could create new paradigms for sustainable energy management.
- **Real-World Deployment and Multi-Objective Optimization:** Conducting large-scale field tests in real driving environments is essential for validating the proposed control strategies under practical constraints such as varying traffic conditions, road topologies, and weather variations. Moreover, implementing real-time multi-objective optimization—balancing energy efficiency, dynamic response, thermal limits, and user comfort—could further refine the control logic.
- **Artificial Intelligence for Predictive and Adaptive Control:** The integration of reinforcement learning, deep neural networks, or hybrid AI systems can offer predictive capabilities and adaptive behavior in unseen conditions. Future work may focus on creating self-learning controllers that continuously evolve based on usage data and environmental feedback, improving system performance over time.
- **Cybersecurity and Data Protection in EV Control Networks:** As control and energy systems become increasingly connected through IoT and cloud platforms, securing communication and control data becomes critical. Future investigations may address the design of secure control architectures that are resilient to cyberattacks, ensuring the integrity, confidentiality, and availability of EV operations.

By exploring these forward-looking directions, researchers can continue to improve the reliability, intelligence, and sustainability of electric vehicles. These advancements will not only

support the technological evolution of smart transportation but also contribute significantly to the broader goals of energy efficiency and environmental responsibility.

7.3 List of Publications

During the course of this doctoral research, several scientific contributions were produced, resulting in publications in peer-reviewed journals, a book chapter, and participations in national and international conferences. These contributions, which are directly related to the research work presented in this thesis, are listed below and classified according to their publication type.

Journal Articles

- **Kethiri, Mohamed Fadi, & Charrouf, O.** (2023). A methodology for fault tolerant control of brushless DC motors with damaged Hall-effect sensors using electronic logic gates. *Journal Européen des Systèmes Automatisés*, 56(3), 431–435.
- **Kethiri, Mohamed Fadi, Charrouf, O., Betka, A., Salman, A., & Boccaletti, C.** (2025). Minimizing power losses in BLDC motor drives through adaptive flux control: A real-time experimental study. *Actuators*, 14(8), 395. MDPI.
- **Kethiri, Mohamed Fadi, Charrouf, O., Betka, A., Tibermacine, I. E., & Napoli, C.** (2025). Hybrid fuzzy-PSO based self-tuning fractional-order PI controller for BLDC motors in electric vehicles: Comparative analysis and experimental validation. *Journal of Vibration and Control*.

Book Chapter

- **Kethiri, Mohamed Fadi, & Charrouf, O.** (2023). State of the art of electrical motors control management system and trends for modern electric vehicles. In Berkan Balpetek (Ed.), *Engineering Sciences in a Globalizing World* (Vol. 1, pp. 5–21). Duvar Design.

International Conferences

- **Mohamed Fadi Kethiri, Omar Charrouf**, “*State of the Art of Electrical Motors Control Management System and Trends for Modern Electric Vehicles*”, 1st International Conference on Trends in Advanced Research, March 4–7, 2023, Konya, Turkey.

- **Mohamed Fadi Kethiri**, Omar Charrouf, “*A New Model Predictive Current and Speed Control Combination for PMSM Using Two Sliding Mode Speed and Flux Weakening Controllers*”, 2nd International Conference on Engineering, Natural and Social Sciences (ICENSOS 2023), April 4–6, 2023, Konya, Turkey.
- **Mohamed Fadi Kethiri**, Omar Charrouf, Malika Hasrouni, “*The Benefits of Model Predictive Control on AC Motors (Review)*”, Second Arab Conference on Mechanics and Engineering (ARCME’23), December 10–12, 2023, University of Biskra, Algeria.

National Conferences

- **Mohamed Fadi Kethiri**, Omar Charrouf, Imad Eddine Tibermachine, “*Reducing Torque and Current Ripples in PMSMs through Integrated Sliding Mode and Predictive Control Techniques*”, National Conference on Artificial Intelligence in Electrical Engineering (NCAIEE’2024), November 13, 2024, Medea, Algeria.
- **Mohamed Fadi Kethiri**, Omar Charrouf, Malika Hasrouni, “*Enhancing PMSM Performance through Integrated Predictive Current, Speed and Sliding Mode Flux Weakening Controllers*”, National Conference of Applied Sciences and Engineering (NCAS’24), November 17–18, 2024, Algiers, Algeria.

Appendix

Motor Parameters	Value	Unit
Rated power P	1250	W
Rated torque T_L	5.97	Nm
Maximum speed ω	209.43	rad/s
Stator resistance R_s	0.77	Ω
Stator phase inductance L_s	0.027	H
Number of pole pairs p	4	-
Moment of inertia J	0.003083	kg·m ²
Damping coefficient B	0.0048577	Ns/m
Maximum voltage V_{dc}	310	V
MHA Parameters in Offline Process	Value	Unit
Number of Iterations (itr)	80	-
Number of Particles or Wolves or Bees (Agents) (N)	100	-
Number of Parameters (var)	3	-
Lower Bound (lb)	[0, 0, 0.1]	-
Upper Bound (ub)	[10, 10, 3]	-
Inertia Weight (wmax) for PSO	0.7	-
Inertia Weight (wmin) for PSO	0.3	-
Simulation time (tsim)	4	s
PSO Parameters in Online Process	Value	Unit
Number of Iterations (itr)	10	-
Number of Particles (Agents) (N)	3	-
Number of Parameters (var)	2	-
Lower Bound (lb) of δ_1 and δ_2	[1e-6, 1e-6]	-
Upper Bound (ub) of δ_1 and δ_2	[1e-4, 1e-4]	-
Inertia Weight (wmax)	0.7	-
Inertia Weight (wmin)	0.3	-
Sampling Time in HIL (Ts)	1e-4	s
Sampling Time in the real test bench (Ts)	1e-3	s
FOPI Controller Parameters	Lower Bound	Upper Bound
Proportional gain K_p	0	10
Integral gain K_i	0	10
Fractional order λ	0.1	3

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