

**Safety and Performance Enhancement
Technologies for PMSM-Based Electric
Powertrains**

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Abstract

The global transition toward electrified transportation has positioned electric vehicles (EVs) as a cornerstone of sustainable mobility, yet the reliability and safety of their powertrains remain critical challenges. This thesis addresses errors within permanent magnet synchronous motor (PMSM)-based electric powertrains, which propagate through tightly coupled subsystems, degrading performance and functional safety. Unlike catastrophic faults, these errors originate from non-idealities in sensors, power electronic inverters, analog-to-digital converters, and microcontrollers during normal operation and when mission-critical components such as inverters and position sensors operate in degraded or fault-tolerant modes. In such scenarios, measurement and estimation inaccuracies become more pronounced and, in multi-motor architectures, are further amplified by interactions between drive units.

Initially, a comprehensive literature review examines error sources in vital powertrain components during regular and fault-tolerant operation. Building on this foundation, three distinct error mitigation strategies are developed. For single-motor PMSM drives, an Enhanced Adaptive Selective Harmonic Annulation algorithm embedded within a Finite Control Set Model Predictive Current Control framework provides unified, real-time compensation for hybrid errors by suppressing harmonic distortions in dq-axis currents. For quad-motor drivetrains, a correlative correction strategy exploits inherent coupling through a shared DC-link, enabling simultaneous estimation and compensation of offset and scaling errors using algebraic relationships between inverter switching states and current flow paths. For dual-PMSM all-wheel-drive powertrains, a robust fault-tolerant framework addresses rotor position sensor failure using a hyperbolic tangent-based sliding mode observer, while a blended weighting transition algorithm enables seamless handover from sensor-based to sensorless operation, leveraging front motor speed feedback to enhance low-speed estimation.

Experimental and comprehensive simulation results establish that system-level error mitigation, rather than component-level isolation, is essential for ensuring the reliability, efficiency, and functional safety of next-generation electrified propulsion systems. The research contributes a comprehensive software-based safety framework addressing sensor imperfections from gradual degradation to complete failure, advancing the development of safer and more dependable EVs.

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Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for a degree or other qualification at this University or elsewhere. All sources are acknowledged as references.

The primary contents of chapter 2 have been submitted to *IEEE Transactions on Transportation Electrification*. Title is “Analysis of the Sources of Error Within PMSM-Based Electric Powertrains—A Review”

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List of Publications

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Abbreviations

EV	Electric Vehicle
ICE	Internal Combustion Engine
HEV	Hybrid Electric Vehicle
PHEV	Plug-In Hybrid Electric Vehicle
PMSM	Permanent Magnet Synchronous Motor
FOC	Field-Oriented Control
DTC	Direct Torque Control
PID	Proportional-Integral-Derivative
MPC	Model Predictive Control
IGBT	Insulated-Gate Bipolar Transistor
MOSFET	Metal-Oxide Semiconductor Field-Effect Transistor
VSI	Voltage-Source Inverter
PWM	Pulse width Modulation
FPGA	Field-Programmable Gate Array
FIR	Finite Impulse Response
BLDCM	Brushless DC Motor
SRM	Switched Reluctance Motor
IM	Induction Motor
IPMSM	Interior Permanent Magnet Synchronous Motor
UMP	Unbalanced Magnetic Pull
SE	Static Eccentricity
DE	Dynamic Eccentricity

ME	Mixed Eccentricity
ILC	Iterative Learning Control
MVIM	Measurement Vector Insertion Method
RDC	Resolver-to-Digital-Converter
SPMSM	Surface-mounted Permanent Magnet
SAR	Successive Approximation Register
DAC	Digital-to-Analog Converter
DNL	Differential Nonlinearity
INL	Integral Nonlinearity
TUE	Total Unadjusted Error
LMS	Least Mean Square
DEC	Digital Error Correction
AVF	Adaptive Vector Filter
CFN	Cross-Feedback Network
ZVV	Zero Voltage Vector
TPFS	Three-Phase Four Switch
TPSS	Three-Phase Six Switch
SVPWM	Space Vector Pulse Width Modulation
SVM	Space Vector Modulation
FFT	Fast Fourier Transform
THD	Total Harmonic Distortion
ADC	Analog-to-Digital Converter
RESS	Rechargeable Energy Storage System
UN	United Nations

GTR	Global Technical Regulation
VCU	Vehicle Control Unit
CAN	Controller Area Network
FCS-MPCC	Finite Control Set Model Predictive Current Control
ASHA	Adaptive Selective Harmonic Annulation
HE	Hybrid Error
ZOH	Zero-Order Hold
CME	Current Measurement Error
ADRC	Active Disturbance Rejection Control
E-ASHA	Enhanced Adaptive Selective Harmonic Annulation
QMD	Quad-Motor Drive
DCA	Distribution Calibration Approach
AWD	All-Wheel-Drive
SMO	Sliding Mode Observer
HFI	High Frequency Injection
EKF	Extended Kalman Filter
MRAS	Model Reference Adaptive System
ML	Machine Learning
DL	Deep Learning

Nomenclature

a_1, b_1	Scaling ratios in motor subsystem 1
c_r	Centre of the rotor
c_s	Centre of the stator
$C_{s/h}$	Internal Sampling capacitor
c_ω	Centre of rotation
$e_{f\alpha,\beta}$	Component of extended EMF associated with the fundamental
$e_{h\alpha,\beta}$	Component of extended EMF associated with the harmonics
$e_{\alpha,\beta}$	Extended EMF in the α -axis and β -axis respectively
$\tilde{e}_{2\alpha}, \tilde{e}_{2\beta}$	Back-EMF estimates
F_{drag}	Aerodynamic drag force
f_e	Stator electrical frequency
HV_{DC}	High DC-bus voltage
i_A	Load current
$i_{AM1_t1_1}, i_{AM1_t1_2}$	Currents sampled by the phase-A current sensor
i_{a_mea}, i_{b_mea}	Measured currents in the abc reference frame
$i_{B1_t3_1}, i_{B1_t3_2}$	Actual phase-B currents in motor subsystem 1
i_{dc}	DC-bus current
$i_{DC1_t1_1}, i_{DC1_t1_2}$	Currents sampled by the DC-bus sensor
i_d, i_q	Stator dq-axis currents
i_{q_ASHA}, i_{d_ASHA}	q-axis and d-axis compensation currents
i'_{A_1}, i'_{B_1}	Compensated phase-A and phase-B currents

i_d^*, i_q^*	d-axis and q-axis reference currents
$\hat{i}_{2\alpha}, \hat{i}_{2\beta}$	Estimated currents
J, B	Moment of inertia, viscous friction coefficient
k_a, k_b	Scaling errors
k_0	Nominal gain
k_t	Torque constant
k_α, k_β	SMO gains
L_d, L_q	d-q stator inductances
L_s	Stator inductance
$L_p^{-1}(z)$	Inverse transfer function of motor plant
M_{DC1}, M_{A1}	Balance coefficients for scaling errors of DC-bus & phase-A currents
$p(k), y(k)$	Primary input signal, Output signal
p_n	Pole pairs
R	Stator resistance
R_{IN}	Analog signal source impedance
$R_{s/h}$	Switch resistance
r_{eff}	Effective wheel radius
S_{1-6}	Six inverter power switches
T_{AD}	Sum of sampling time and analog to digital conversion time.
T_{delay}	Delay time associated with the IGBT turn-on or turn-off time
T_e, T_l	Electromagnetic torque, Load torque
T_{min}	Minimum sampling time
$T_{offset}, T_{scaling}$	Torque harmonics caused by offset error and scaling error respectively

T_s	PWM cycle/sampling period
T_{sett}	Current settling time
T_e^*	Reference torque
t_d	Dead-time
t_{fail}	failure detection time
t_{3_1}, t_{3_2}	Sampling points
V_{AREF}	Reference voltage
V_{AO}, V_{BO}, V_{CO}	Pole voltages
V_{dc}	DC source voltage
V_{err}	Average error pole voltage
V_{in}	Battery voltage
V_0	Inverter output voltage
v_s	Actual stator voltage vector
v_s^*	Reference stator voltage vector
$V_{\alpha,\beta}, i_{\alpha,\beta}$	Stator voltages and currents (in the α, β stationary reference frame)
$x_a(k), x_b(k)$	Sinusoidal reference currents
δ_ω	Speed synchronization threshold
$\varepsilon_{rr}(k)$	Error estimate
$\varepsilon_\theta, \varepsilon_\omega$	Residual-based thresholds
ξ, μ	Mean square error, adaptation gain constant
η_f, η_r	Front and rear wheel radii
λ_f	Rotor flux
λ_s	Stator linkage flux

$\omega_a(k) \ \omega_b(k)$	Adaptive weights
ω_e	Electrical rotor speed
$\hat{\omega}_{rear}$	Estimated rear motor electrical speed
$\hat{\omega}_r^{SMO}$ or $\hat{\omega}_{r2}$	SMO-estimated rear motor speed
$\theta_r, \theta_s, \theta_v$	Rotor flux position, Stator flux position, Stator voltage position
$\hat{\theta}_e$	Estimated rotor position
$\hat{\theta}_{ei}$	Initial phase angle of the rotor position observation
$\alpha(t)$	blending factor or dynamic weighting factor
$\Delta i_{a_offset}, \Delta i_{b_offset}$	Offset errors in the abc reference frame
ψ_{PM}	Permanent magnet flux linkage
ζ_1, ζ_2	Disturbance torques

Chapter 1 Introduction

1.1 Background

1.1.1 Electrification of the Transportation Sector

The global transportation sector is undergoing a profound technological transformation as societies transition away from fossil-fuel-dependent mobility toward electrified transportation systems. This transition is largely driven by the urgent need to mitigate greenhouse gas emissions, improve urban air quality, and reduce dependence on petroleum-based fuels. The transportation sector contributes approximately one quarter of global carbon dioxide emissions, with road vehicles constituting the dominant share [1]. Consequently, the electrification of road transport has emerged as a central strategy for achieving long-term decarbonisation goals.

Electric vehicles (EVs) have become the cornerstone of this transformation. Advances in rechargeable energy storage systems, high-efficiency electric machines, and power electronic converters have enabled EVs to achieve competitive performance relative to internal combustion engine vehicles (ICEVs). EVs offer numerous advantages including high energy conversion efficiency, reduced maintenance requirements, and zero tailpipe emissions [2]. As a result, global EV adoption has increased rapidly over the past decade, supported by regulatory policies, technological innovation, and increasing public awareness of environmental sustainability.

Despite these advantages, the large-scale deployment of EVs introduces new engineering challenges that differ significantly from those associated with conventional vehicles. Unlike ICE-based systems that rely heavily on mechanical processes, EVs depend primarily on tightly integrated electromechanical and electronic subsystems. These systems require precise control, real-time feedback, and high-speed signal processing. Consequently, the reliability and safety of EVs are closely linked to the robustness of their electric powertrains.

1.1.2 Electric Vehicle Powertrain Architecture

The electric powertrain forms the core propulsion subsystem of an EV, responsible for converting electrical energy into mechanical torque that drives the vehicle's wheels. A typical EV powertrain comprises several tightly integrated components, including:

- A high-voltage battery pack
- Power electronic converters and inverters
- Electric traction motors
- Current, voltage, and position sensing systems
- Embedded microcontrollers executing control algorithms
- Vehicle control units and communication interfaces

The simplified block diagram for the BEV is shown in Fig. 1-1, depicting some of its major components. In the diagram, V_0 , V_{in} and HV_{DC} represent the inverter output voltage, the battery voltage and the high voltage of the DC bus respectively.

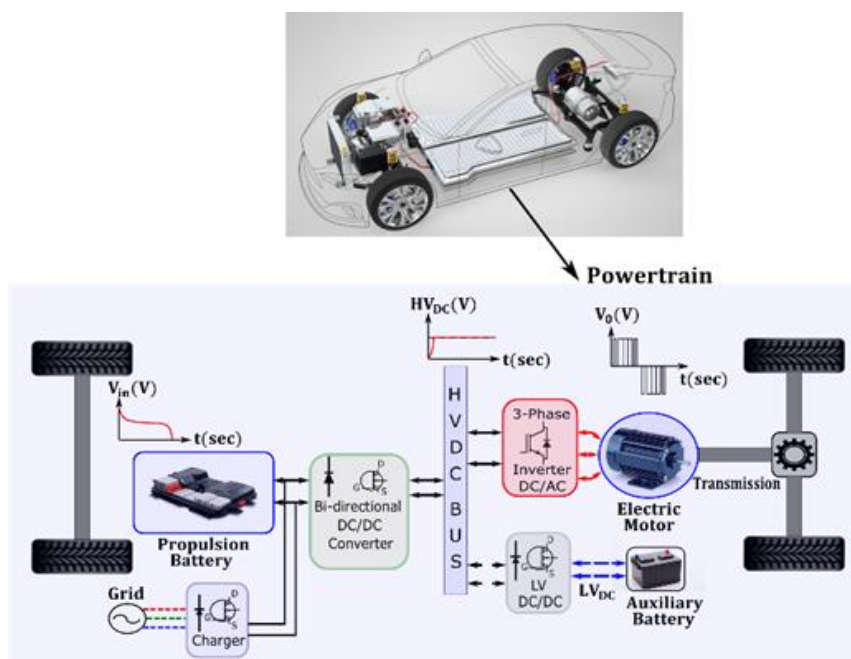


Fig. 1-1. Block diagram for EV powertrain.

In battery electric vehicles (BEVs), electrical energy stored in the battery pack is delivered to a voltage source inverter via a high-voltage DC-link. The inverter converts the DC voltage into

three-phase AC waveforms that drive the electric traction motor. The motor subsequently converts electrical energy into mechanical torque, which is transmitted through the drivetrain to propel the vehicle.

The operation of this system relies on closed-loop control architectures that require continuous feedback from sensors measuring quantities such as rotor position, motor current, speed, and voltage. These measurements are processed by embedded controllers implementing advanced control algorithms that regulate torque production, optimise efficiency, and ensure stable operation under varying driving conditions.

Because these subsystems are tightly coupled through real-time control loops, disturbances or errors originating in any component may propagate throughout the entire powertrain system.

1.1.3 Types of Electric Vehicle Powertrain Configurations

Electric vehicle propulsion systems can be categorised according to their degree of electrification and drivetrain architecture [3].

Battery Electric Vehicles (BEVs) rely entirely on electric propulsion powered by rechargeable battery packs. These vehicles represent the most direct implementation of electric mobility and exhibit the highest drivetrain efficiency.

Hybrid Electric Vehicles (HEVs) combine internal combustion engines with electric propulsion systems to improve fuel efficiency and reduce emissions. They can be parallel, series, or series-parallel hybrids. Series hybrids use the engine primarily as a generator to charge the battery, while parallel hybrids can transmit mechanical power from both the motor and engine directly to the wheels.

Plug-in Hybrid Electric Vehicles (PHEVs) incorporate larger battery packs that enable extended electric-only driving before transitioning to hybrid operation.

Fuel Cell Electric Vehicles (FCEVs): Use a fuel cell to generate electricity from energy stored as hydrogen, which then powers an electric motor. They produce only water vapour and warm water as by-products and offer faster refuelling, longer ranges, and scalability, making them a practical path to decarbonizing transportation [4].

In addition to these classifications, EV powertrains may also be distinguished by the number of electric motors used within the drivetrain. Modern EV architectures increasingly employ

multi-motor propulsion systems, such as dual-motor or quad-motor drivetrains, which allow independent torque control at individual wheels. These configurations offer significant advantages in terms of traction control, torque vectoring, and vehicle stability. However, the distributed nature of these systems increases control complexity and introduces additional sources of error that must be carefully managed [5].

1.1.4 Electric Traction motors in EV Applications

Electric traction motors are central to EV propulsion systems. Several motor technologies have been adopted in electric vehicle applications, including induction motors, brushless DC motors, switched reluctance motors, and permanent magnet synchronous motors (PMSMs).

Among these technologies, permanent magnet synchronous motors (PMSMs) have emerged as the dominant choice for modern EV powertrains due to their high power density, superior efficiency, and excellent dynamic response [6], [7]. PMSMs are capable of delivering high torque at low speeds and maintaining efficient operation across a wide speed range, making them well suited for automotive propulsion. These motors work in tandem with other units to enhance smooth electric propulsion. Nevertheless, errors emerge within the powertrain to mar this alliance. An error is the difference between a quantity's measured value and its actual value. A fault, on the other hand, refers to an unpermitted deviation of at least one characteristic property of a system from acceptable or standard conditions. Under normal operating conditions, EV components work at expected current and voltage settings, however once the accumulation of error becomes significant, the deviations from the desired current and voltage ratings manifest as undesirable speed fluctuation, torque ripple and unbalanced phase currents throughout the electric powertrain. The complexity of the EV powertrain makes it challenging to single out a component for replacement, hence early detection of errors at incipient stages could safeguard the drivetrain in the grand scheme of things.

They are typically controlled using advanced vector control strategies such as field-oriented control (FOC) or model predictive control (MPC), both of which rely on accurate measurements of rotor position and stator currents. Consequently, the performance of PMSM drives is highly sensitive to measurement errors, parameter variations, and inverter non-idealities.

1.1.5 Functional safety in Electric Vehicle Powertrains

Functional safety refers to a system's ability to maintain safe operation even in the presence of faults or abnormal operating conditions. In the context of EV powertrains, functional safety ensures that propulsion systems continue operating within safe limits despite component errors or partial failures. As EVs increasingly rely on electronically controlled propulsion systems, ensuring functional safety has become a critical requirement in automotive design.

The automotive industry has established comprehensive safety standards governing the design and verification of electronic control systems. One of the most widely adopted frameworks is ISO 26262, which defines safety lifecycle processes for automotive electrical and electronic systems. ISO 26262 introduces the concept of Automotive Safety Integrity Levels (ASILs), which classify system components according to the severity, exposure, and controllability of potential hazards [8]. The automotive industry's adoption of ISO 26262 (functional safety) has forced a shift from reactive fault handling to proactive safety mechanisms.

In addition to ISO 26262, regulatory frameworks such as UNECE Regulation No. 100 address the safety of high-voltage electric powertrains in road vehicles, including requirements for electrical isolation, battery safety, and system protection. These safety frameworks highlight the importance of robust system design, fault detection mechanisms, and fault-tolerant control strategies to ensure safe vehicle operation.

1.2 Literature Review

The performance, reliability, and functional safety of EV powertrains have been the subject of extensive research, particularly as modern propulsion systems become increasingly dependent on tightly coupled electromechanical and digital control subsystems. Existing studies have primarily addressed three interconnected aspects: the detection and diagnosis of faults, the characterisation of error sources within key powertrain components, and the development of control and fault-tolerant strategies to mitigate their effects. However, these areas are often investigated in isolation, despite the inherently integrated nature of EV powertrains.

1.2.1 Fault Detection and Diagnosis

The ability to accurately detect and diagnose faults is fundamental to ensuring safe and reliable EV operation. Among the various approaches proposed in literature, model-based techniques have received considerable attention due to their ability to provide analytical insight into system behaviour. These methods rely on mathematical models of the powertrain to generate expected system responses, which are then compared with measured signals. Any deviation between predicted and observed behaviour is interpreted as an indicator of abnormal operation [9], [10].

Observer-based techniques form a key component of model-based fault detection frameworks. Observers such as sliding mode observers, Luenberger observers, and Kalman filter-based estimators are employed to reconstruct system states that are not directly measurable. By comparing estimated states with actual sensor measurements, residual signals can be generated and evaluated for fault detection purposes. While these approaches are effective in identifying sensor faults, actuator anomalies, and parameter deviations, their performance is strongly dependent on model accuracy and robustness to uncertainties.

In parallel, signal processing techniques have been widely adopted to detect fault signatures directly from measured signals (motor current, voltage, and speed signals). Methods based on frequency-domain and time-frequency analysis, such as Fourier transforms and wavelet decomposition, are commonly used to extract harmonic components associated with specific fault conditions [11], [12]. These techniques are particularly effective in identifying mechanical and electromagnetic faults. However, such approaches are often reactive in nature and may face challenges in distinguishing between multiple concurrent fault sources or in providing early-stage fault prediction. The transition from general fault detection to a granular analysis of error origins within EV powertrain components has become necessary due to the increasing complexity and tight coupling of modern electrified systems. While traditional model-based fault detection focuses on identifying major system failures, modern safety requirements demand the identification of errors at their budding stages to prevent them from cascading into system-wide failures. Analysing the origins of errors allows engineers to capture deviations before they manifest as faults or a complete system failure.

1.2.2 Sources of Error in EV Powertrain Components

A critical aspect of EV powertrain analysis lies in understanding the physical origins of errors that degrade system performance. Among the various subsystems, power electronic inverters represent a significant source of non-ideal behaviour. Practical inverters exhibit switching-related nonlinearities, including dead-time effects, semiconductor voltage drops, and propagation delays. These non-idealities distort the output voltage waveforms, leading to current harmonics, torque ripple, and reduced overall efficiency. Such distortions are particularly problematic in high-performance traction applications where precise torque control is required.

Electric machines themselves are also subject to inherent imperfections arising from manufacturing tolerances and operational conditions. Rotor and stator eccentricities, which may be static, dynamic, or mixed in nature, introduce air-gap asymmetries that result in unbalanced magnetic forces. These forces give rise to torque oscillations, increased vibration, and acoustic noise, all of which contribute to mechanical stress and long-term reliability concerns. Due to the complexity and depth of analysis required to handle motor errors, they have been briefly raised in the literature review section without any validating experiments or simulations.

The sensing subsystem constitutes another critical source of error within EV powertrains. Accurate measurement of currents and rotor position is essential for effective closed-loop control. However, current sensors are susceptible to offset and gain errors, while position sensing devices such as resolvers may exhibit amplitude imbalances, phase shifts, and conversion inaccuracies within resolver-to-digital converters. These measurement errors propagate directly into the control loop, leading to distorted current regulation and degraded torque production.

In addition to hardware-related issues, embedded control platforms introduce further limitations. Analog-to-digital converters and microcontrollers are affected by quantisation errors, nonlinearities, reference voltage instability, and temperature-dependent drift. Moreover, sampling delays and timing mismatches within digital control systems can introduce phase lag, further compromising system stability and dynamic response. Collectively, these factors contribute to a complex error landscape in which multiple sources interact and influence overall system behaviour. Fig. 1-2 depicts potential sources of error within the closed-loop operation.

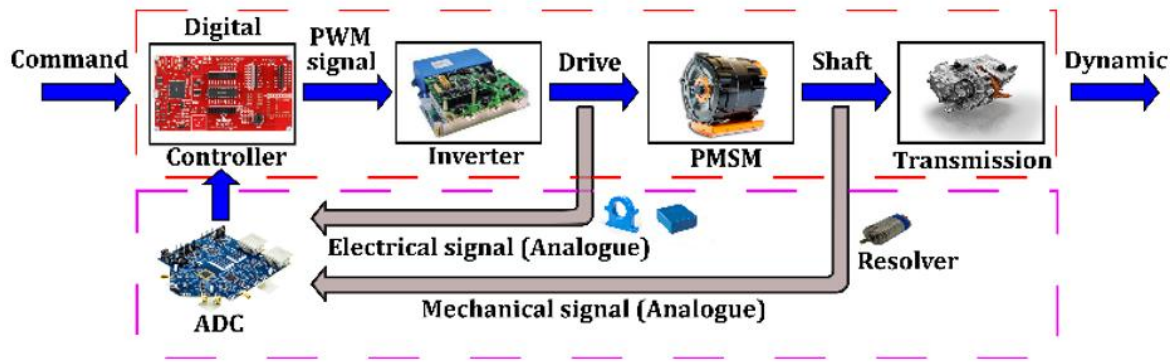


Fig. 1-2. Scrutiny of the effect of errors within the closed-loop control of the drivetrain.

1.2.3 Fault-Tolerant Operation and Control Strategies

To address the impact of component-level errors and ensure safe operation, a range of fault-tolerant control strategies has been proposed in the literature. One widely adopted approach involves the use of redundancy, either in hardware or in analytical form. Hardware redundancy typically involves the use of additional sensors or parallel subsystems to provide backup functionality in the event of failure. While effective, this approach increases system cost and complexity. Alternatively, analytical redundancy utilises software-based estimation to replace faulty sensor data to maintain operation after a component failure.

Another important strategy involves system reconfiguration in response to detected faults. In such cases, the control system adapts its structure or operating mode to maintain safe operation under degraded conditions. For example, in the event of a position sensor failure, the system may transition to a sensorless control mode based on estimated rotor position. Similarly, control laws may be modified to accommodate reduced system capability or altered operating constraints. These reconfiguration strategies are essential for maintaining continuity of operation, particularly in safety-critical applications [13], [14].

Fault-tolerant inverter topologies and modified switching strategies have also been investigated as a means of ensuring continued operation under power electronic failures [15], [16]. In parallel, sensorless control techniques based on observer design have been extensively developed to eliminate dependence on physical position sensors [17], [18]. While these methods provide a viable alternative under fault conditions, their performance is often limited by sensitivity to parameter variations and reduced accuracy at low speeds. Furthermore, achieving smooth and stable transitions between sensor-based and sensorless operation remains

a significant challenge, as abrupt switching can introduce torque disturbances and compromise system stability.

1.2.4 Mitigation of Current Measurement Errors (CMEs) and System-Level Challenges

Within the context of single-motor electric drives, considerable effort has been devoted to mitigating the effects of CMEs and associated delays. Existing approaches include offline calibration techniques, observer-based estimation methods, harmonic suppression strategies, and topology-driven solutions that exploit inverter switching states. While these methods can improve steady-state performance, they often rely on fixed assumptions, require additional computational resources, or disrupt normal control operation. As a result, their ability to address time-varying conditions remains limited.

The challenges become more pronounced in multi-motor EV powertrains, where multiple drive units must operate in a coordinated manner. In such systems, CMEs are not confined to individual motors but instead propagate across the entire drivetrain. This leads to compounded effects such as phase current imbalance, loss of synchronisation, and uneven torque distribution. Although significant research has been conducted on torque vectoring and vehicle dynamics in multi-motor configurations, relatively little attention has been given to the systematic calibration and correction of CMEs across distributed drive systems. This represents a critical limitation, particularly in high-performance and safety-critical applications.

In the area of fault-tolerant control, sensorless algorithms have been widely explored as a means of maintaining operation under position sensor failure. While these approaches are well established for single-motor systems, their extension to dual-motor or multi-motor configurations introduces additional complexity. Issues such as inter-motor synchronisation, robustness to parameter variation, and transient stability during fault conditions become increasingly significant. Existing methods often struggle to achieve seamless transitions between sensor-based and sensorless modes, resulting in torque ripple and performance degradation during switching events.

1.2.5 Research Gaps, Motivation and Objectives

The foregoing discussion highlights several key limitations in the current state of the art. First, existing research largely treats error sources independently, without adequately considering their combined effects within integrated EV powertrain systems. Second, many compensation techniques lack adaptability and are unable to effectively address time-varying conditions. Third, the impact of CMEs in multi-motor architectures remains insufficiently explored, despite the growing adoption of such configurations in modern EVs. Finally, fault-tolerant control strategies continue to face challenges in achieving smooth and reliable operation under sensor failure, particularly in systems involving multiple coordinated drives.

These limitations provide the primary motivation for the research presented in this thesis. In particular, the work seeks to develop integrated, adaptive, and system-level solutions capable of addressing the complex interactions between errors in EV powertrains. The approaches proposed in subsequent chapters aim to enhance performance, improve reliability, and ensure safe operation under both normal and degraded conditions. Simply put, the research aims to explore the impact errors from cardinal EV powertrain components ultimately have on performance, reliability, and EV safety and to develop advanced control strategies capable of mitigating the risks associated with EV powertrain failures.

The research objectives guiding this thesis are as follows:

- i) To provide a comprehensive examination of error sources in key powertrain components (inverter, motor, sensors, microcontroller) in both normal and degraded modes and their impact on safety, reliability, and system performance.
- ii) To develop an enhanced adaptive selective harmonic annulation (ASHA) scheme to suppress current harmonics due to hybrid errors (sensor offsets/delays) in SPMSM drives, with real-time coefficient adaptation.
- iii) To propose a correlative correction strategy capable of compensating for CMEs in quad-motor electric powertrains.
- iv) To introduce a resilient control framework for dual-PMSM AWD powertrains featuring a hyperbolic tangent sliding mode observer (SMO) with a blended sensor/sensorless transition, leveraging front-motor speed feedback to improve rear-motor estimation and ensure continuous torque generation under sensor failure.

1.3 Thesis Layout and Chapter Contributions

This dissertation is structured into six chapters, each contributing to the overarching research aims and motivation by addressing specific aspects of EV powertrain error mitigation. The overview is as follows:

Chapter 1: Introduction

Contribution: Introduces the motivation for this study, provides essential background on EV powertrains and safety, reviews the current state of the art in error mitigation, identifies research gaps, and outlines the research aims and objectives. This chapter sets the stage for the subsequent detailed investigations.

Chapter 2: Literature Review

Contribution: This chapter delves into how errors from critical powertrain components (power electronic inverters, electric motors, sensors, and microcontrollers) originate and ultimately compromise vehicle safety during both normal and fault-tolerant modes of operation. It provides a foundational understanding of the error sources that the thesis aims to mitigate.

Chapter 3: Suppression of SPMSM-Based Powertrain Hybrid Errors Using Adaptive Filters Integrated within FCS-MPC Controllers

Contribution: Designs an enhanced adaptive selective harmonic annulation algorithm to selectively cancel specific harmonics within input motor current signals that contribute to torque and speed pulsations. This directly addresses the impact of hybrid errors on performance and reliability, aligning with the objective of developing robust detection and mitigation techniques.

Chapter 4: Correlative Correction of CMEs for Quad-Motor Electric Drivetrains

Contribution: Presents a correlative correction strategy for compensating CMEs in quad-motor electric drivetrains using a distributed calibration technique. The approach enables independent CME correction for each motor with minimal disruption to routine control, validated experimentally under electromagnetic interference and dynamic loads.

Chapter 5: A Blended Weighting Sensor/Sensorless Transition Strategy for Dual-PMSM Drives under Position Sensor Failure

Contribution: Designs a robust position sensor error control algorithm for dual PMSM All-Wheel Drive (AWD) electric powertrains, wherein the rear (more powerful motor) operates under sensorless control in the event of a position sensor failure. To address the inherent challenges of sensorless estimation at low speeds and during uphill transitions, the scheme utilizes the front motor's vehicle speed feedback to enhance observer convergence.

Chapter 6: Conclusion and Future Work

Contribution: Summarizes the key findings and contributions of the thesis, reiterates how the research objectives have been met, and discusses future tasks that can be implemented to upgrade safety and performance enhancement technologies for EVs.

1.4 Summary

This introductory chapter has established a foundational understanding of EV powertrain structures and the profound impact that errors from key components can have on functional safety. By reviewing the current state-of-the-art and identifying key research gaps, the chapter has motivated the need for comprehensive error mitigation strategies. The outlined research aims and objectives, along with the detailed thesis layout, demonstrate a structured approach to addressing these challenges, ultimately contributing to the development of safer and more dependable electric vehicles.

Chapter 2 Literature Review

This chapter reviews the evolution of electric vehicle (EV) powertrains, focusing on the increasing importance of system-level accuracy, reliability, and robustness. Unlike early studies that primarily addressed component-level faults, recent research recognises that non-idealities in sensing, modelling, and computation introduce errors that propagate across tightly coupled subsystems, significantly affecting overall drive performance. The chapter highlights this paradigm shift from isolated fault analysis to a more integrated perspective centred on error sources, their interactions, and their impact on control and system stability. In this context, a detailed analysis is presented on how errors originate during normal operation from key components, such as power electronic inverters, analog-to-digital converters, resolvers, electric motors, and current sensors during regular modes of operation. Furthermore, the chapter examines configurational errors that arise when components such as inverters and position sensors adopt fault-tolerant topologies.

A comprehensive review of modern EV motor drive architectures is presented, covering the transition from conventional single-motor systems to multi-motor and highly integrated electric drive units (e-axes). Advances in control strategies, including model-based and predictive approaches, are examined alongside their sensitivity to parameter uncertainties and measurement inaccuracies. In parallel, developments in power electronics, particularly the adoption of wide bandgap semiconductor devices and high-voltage platforms, are discussed in relation to efficiency improvements and increased system complexity. The chapter also surveys the principal electric machine technologies used in EV applications, comparing their operational characteristics, advantages, and limitations. Collectively, the literature underscores that as EV systems become more integrated and performance-driven, they also become more susceptible to error propagation. This necessitates the development of robust estimation, compensation, and control strategies to ensure reliable and safe operation under real-world conditions.

2.1 Introduction

The rapid development of electric vehicles (EVs) has placed the electric powertrain at the centre of vehicle performance, efficiency and safety. This powertrain typically comprises

electric machines, power electronics inverters, sensing units and embedded control systems, all of which operate in a tightly coupled, closed-loop architecture. Within such systems, deviations from ideal behavior do not arise solely from catastrophic faults, but also from errors, defined as discrepancies between measured, estimated, or computed variables and their true values, which can propagate through the system and degrade overall performance.

In contrast to faults, which are generally associated with physical defects or failures in components, errors often originate from non-idealities such as sensor inaccuracies, quantization effects, parameter mismatches, switching nonlinearities in inverters, and numerical limitations in microcontroller implementations. These errors may exist under nominal operating conditions and, although individually small, can accumulate and interact across subsystems, leading to significant deviations in torque production, efficiency, and dynamic response.

Early research in EV powertrains predominantly focused on nominal performance, that is, maximizing efficiency, torque density, and power-to-weight ratios. Consequently, the literature from this period treated component-level faults largely in isolation. For instance, open-circuit faults in inverter switches were studied for their immediate impact on motor current distortion [19], [20], while demagnetization in PMSMs was analyzed through the lens of torque ripple [21], [22]. However, with the maturing of EV technology and the push towards higher voltages (e.g., 800V systems), higher power densities, and autonomous driving, the research focus has fundamentally shifted. The contemporary challenge is no longer just about designing for nominal performance, but about ensuring functional safety (ISO 26262), reliability, and resilience throughout the vehicle's lifecycle, especially under real-world operating conditions where components are subjected to severe electrical, thermal, and mechanical stresses.

This paradigm shift has given rise to a new, more integrated body of literature that recognizes the electric powertrain not as a collection of discrete components, but as a unified electro-mechanical-thermal system. Within this systems-level view, the concept of an 'error' has evolved from a simple component fault to a complex phenomenon. A critical insight from recent literature is that the propagation and interaction of these disparate errors across component boundaries often pose a greater threat to system-level integrity than the initial error itself. For example, a minor current sensor offset error, if unmitigated, can manifest as a steady-state torque error, leading to unintended vehicle behaviour. In a more critical scenario, a

position sensor error can cause a loss of field-oriented control, leading to rapid overcurrents that can destroy the inverter. Consequently, recent research has increasingly focused on understanding, modelling, and mitigating error sources within electric powertrains, alongside traditional fault-oriented approaches. Emphasis has been placed on robust control design, error compensation techniques, and advanced estimation methods to ensure that system performance remains within acceptable bounds despite the presence of inherent inaccuracies.

2.1.1 Motor Drives in EV Applications

The landscape of motor drives for electric vehicle applications has evolved rapidly beyond the traditional single-motor, central-drive architecture. Contemporary EV powertrains are characterised by increasing diversity in motor configuration, sophistication in control strategies, adoption of advanced semiconductor technologies, and a drive toward higher levels of system integration. These developments collectively aim to enhance vehicle performance, reliability, safety, and energy efficiency, while also addressing the growing demands of vehicle segmentation and platform modularity.

One of the most notable developments in EV propulsion is the diversification of motor configurations. Contemporary EVs employ architectures ranging from single-motor centralised drives, typically used in cost-sensitive applications, to dual-motor systems that enable all-wheel drive and improved traction performance. More advanced configurations, such as tri- and quad-motor systems, are increasingly explored to provide enhanced torque vectoring, improved vehicle dynamics, and a degree of redundancy that supports fault-tolerant operation and limp-home capability. Additionally, In-wheel motors represent the most extreme form of distributed propulsion, with motors housed directly within the wheel hub. This architecture eliminates the need for gearboxes, differentials, and driveshafts, freeing cabin space and enabling novel vehicle packaging. While offering exceptional torque vectoring capability and powertrain efficiency, in-wheel motors face significant challenges related to unsprung mass, sealing against environmental ingress, and thermal management under sustained high-load operation [23]. Despite these challenges, ongoing research and niche production applications continue to advance the viability of this architecture.

In addition to architectural variations, a dominant trend in contemporary EV development is the pursuit of highly integrated electric drive units (EDUs), moving from discrete components toward tightly packaged, multifunctional units, commonly referred to as e-axes. The e-axle (or

electric axle) integrates the motor, inverter, and gearbox into a single, compact assembly that can be mounted directly onto the vehicle axle. This approach reduces weight, simplifies assembly, minimises wiring harness complexity, and optimises thermal management by sharing cooling systems across components [24]. More recently, this integration trend has extended toward so-called “X-in-1” architectures, where multiple subsystems including onboard chargers, DC–DC converters, and power distribution units are consolidated within a unified platform. Such approaches aim to reduce cost and improve manufacturability, while simultaneously increasing system-level reliability through reduced component count and simplified interfaces.

Control strategies in modern EV motor drives have also undergone significant advancement, moving beyond conventional torque and speed regulation toward intelligent and fault-aware control frameworks. Techniques such as field-oriented control and direct torque control have been further enhanced through model predictive and optimisation-based approaches, enabling improved dynamic response and efficiency under varying operating conditions. Perhaps most critically from a safety perspective, limp-home functions have become a standard requirement in automotive motor drives. These fault-tolerant control strategies enable continued vehicle operation, albeit at reduced power following the detection of a component breakdown. For instance, in the event of a position sensor failure, sensorless control algorithms can estimate rotor position from current and voltage measurements, allowing propulsion to continue until the vehicle can be safely serviced [25]. Similarly, upon detection of an inverter phase failure, the control strategy can reconfigure to operate the motor with the remaining healthy phases, providing sufficient torque for limited mobility. These functions are integral to achieving the functional safety goals mandated by standards such as ISO 26262.

Parallel to these developments, significant progress has been made in power electronic technologies, particularly with the adoption of wide-bandgap (WBG) semiconductor devices such as silicon carbide and gallium nitride. Compared to conventional silicon IGBTs, WBG semiconductors enable higher switching frequencies, reduced losses, and improved thermal performance, thereby contributing to increased efficiency and power density in EV motor drives [26]. These advancements have facilitated the transition from traditional 400 V architectures to 800 V systems, which allow for reduced current levels for a given power output, leading to lower conduction losses, improved thermal behaviour, and lighter cabling. Furthermore, high-voltage architectures support ultra-fast charging capabilities and sustained

high-performance operation, making them increasingly prevalent in next-generation EV platforms [27].

While these technological advancements significantly enhance the performance and efficiency of EV motor drives, they also introduce increased system complexity and tighter coupling between subsystems. As a result, modern motor drives are more susceptible to the propagation of errors originating from sensing, control, and power electronic components. Highly integrated architectures reduce physical interfaces but increase functional interdependencies, meaning that localised inaccuracies can have system-wide effects. Similarly, advanced control strategies rely heavily on accurate models and high-fidelity measurements, making them inherently sensitive to parameter variations and measurement errors. Consequently, the design of state-of-the-art EV motor drives must not only prioritise performance optimisation but also ensure robustness against error sources that can degrade reliability, efficiency, and safety.

Fig. 2-1 provides an overview of potential sources of error within some primary units utilized in the closed-loop control of the drivetrain. Within Fig. 2-1, the text boxes underneath the motor describe the software tools used to model electric machines and the different types of machines respectively. Likewise, underneath the power inverter, the text box labelled Devices refers to the different kinds of transistors used for switching action, while the text box labelled Topology refers to the various kinds of configurations the device could assume in its operation. The software content of the controller refers to algorithms written in programming languages that define its functionality, while the contents of the textbox labelled Hardware refer to tangible components within the controller responsible for the manipulation of electrical signals.

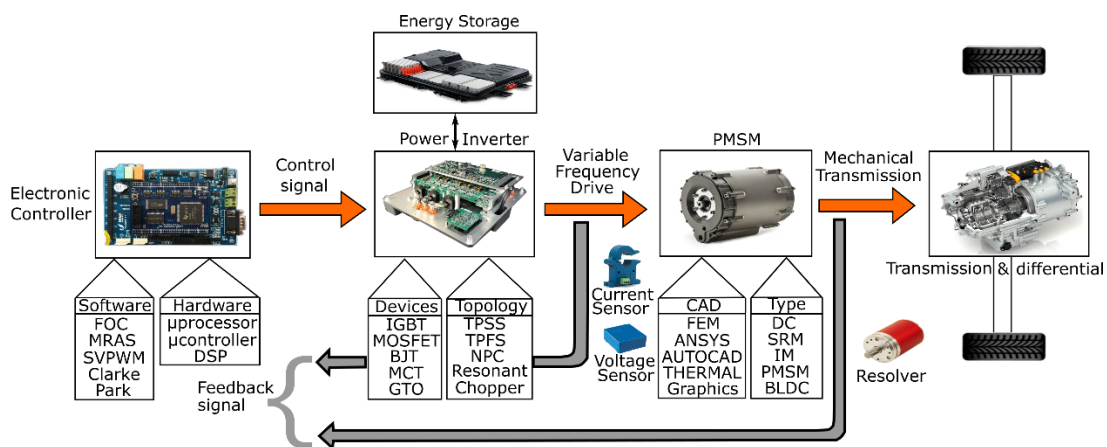


Fig. 2-1. Evaluation of the sources of error within the modern PMSM-based EV powertrain.

2.1.2 Electric Motors in EVs

Another crucial component of the EV powertrain is the electric machine (motor). Its primary objective is to convert electrical energy into kinetic energy to power the wheels. It plays a pivotal role in achieving the best possible drive range, just as the battery does. A good drive range has a direct link to excellent motor/machine efficiency (in essence how good the motor is at converting electrical energy into mechanical energy). Typical requirements desired to be in motors for EV applications include high power, high torque, wide speed range, high efficiency, low noise, robustness, high reliability and flexible structure [28]. EVs use traction motors that can deliver torque to the wheels. Electric motors can be roughly divided into two types: DC and AC motors. Both types can be used in EV applications. DC motors are robust and allow simple control. They can be made as brushed and brushless DC motors. Brushed DC motors are a mature technology that provides low cost, high torque at low speed and easy speed control. These features are important for traction motors. Brushless DC motors on the other hand have a much higher efficiency since they use an electronic commutator/inverter instead of brushes. Compared to DC motors, the advantages of AC motors are high efficiency, less maintenance, higher reliability and regenerative capability that enables braking energy to be returned to the batteries [29]. With the advancement of power electronics and control systems, different AC motors have emerged to meet the needs of the automotive industry. These include induction motors (IMs), permanent magnet (PM) brushless DC motors (BLDCMs), permanent magnet synchronous motors (PMSMs) and switched reluctance motors (SRMs).

a) DC Motors: The stator is composed of two or more permanent magnet pole pieces, and the rotor is composed of windings which are connected to a mechanical commutator. The advantages of these motors are that they can provide maximum torque in low-speed instances. Their limitations reflect in their bulky structure, low efficiency, large heat generation and the adoption of brushes. The heat that is generated in the center of the rotor is difficult to dissipate, consequently brushed DC motors are not utilized in EVs in the current industry [30].

b) Induction Motors (IMs): IMs were widely used in early EVs like the GM EV1 in the mid-nineties and still find a place in current models like the Tesla Model S. Amongst the different AC motor drive systems, the IM is the most maturely developed model [28]. The FOC algorithm has been instrumental in empowering IM drives to meet the requirements of EV systems. The algorithm enables the IM to act as a separately excited DC motor through decoupling of flux and torque producing currents.

c) Brushless DC Motors (BLDCMs): PMs are installed in the rotor of this type of motor and the stator is provided with AC current from the battery through an inverter. As no winding is involved in the rotor, rotor copper loss is negligible, which makes their efficiency higher than IMs. This motor is also lighter, smaller, better at heat dissipation and more reliable. It provides larger torque density and more specific power. The mechanical forces and magnet prices are the biggest disadvantages of this type of motor. The increased centrifugal forces caused by higher motor rotation speed can cause safety issues due to the possible breaking of the magnets [29]. In terms of the PM configurations within the rotor of these kinds of machines, they can be either buried inside the rotor or mounted on its surface.

d) Permanent Magnet Synchronous Motors (PMSMs): These machines are some of the most advanced, capable of operating at a wide range of speeds without using any gear system [31]. Like BLDCMs, these also have PMs in the rotor. Unlike BLDCMs which have a trapezoidal back electromotive force (EMF) waveform, PMSMs have a sinusoidal back EMF. They have a simple construction, high efficiency and high-power density, thus making them suitable to be used as traction motors. PMSMs have higher efficiency compared to IMs. Their limitations include high costs and eddy current losses in the PMs at high speeds. Concerning motor configuration, PMSMs can be classified as surface-mounted PMSM (SPMSM) and interior PMSM (IPMSM).

e) Switched Reluctance Motors (SRMs): The operation of this type of motor is based on the principle of reluctance torque. No windings, slip rings and PMs are employed on the rotor and only a simple concentrated field winding is mounted on the stator. Their advantages in EVs include their robustness, simple control, high efficiency, wide constant power operation region, fault tolerance and effective torque-speed characteristics. Since they do not contain brushes, collectors or magnets, their maintenance is very simple and effective. The absence of magnets eliminates the problem with mechanical forces, enabling the motor to operate at high speeds. Since the motor's windings are not used, there are no copper losses in the rotor ensuring the rotor temperature is lower compared to other motor types. Again, since the phases are unconnected, SRMs can continue their operation even when one of the phases disconnects. SRMs have a lower inertia than other motor types. Their drawbacks include vibration and acoustic noise [32]. Additionally, the salient-pole rotor and stator construction cause high torque ripple [33]. Table 2-1 summarizes the advantages and disadvantages of the motor types discussed. PMSMs tend to be the best choice for high performance motor drive applications

due to their higher-ranking efficiency, compact nature and being light weight. Though PMSMs have attracted lots of attention over the last couple of decades due to superior properties, they are not invulnerable to various errors of electrical (stator windings), magnetic (permanent magnet demagnetization) or mechanical (bearings, imbalance, eccentricity) nature caused by various stresses witnessed during lengthy operation in severe conditions. Due to such harsh exposure, electrical machines are susceptible to exhibiting abnormal behaviour at some point in their operational lives.

TABLE 2-1 Advantages and Disadvantages of Traction Motors and their Applications

Motor types	Advantages	Disadvantages	Vehicle models
DC motor	• Large torque at low speed	• Bulky structure • Low efficiency • Use of Brushes	• Fiat Panda Elettra (BEV) • Conceptor G-Van (BEV)
IM	• Mature technology • High control performance • Robust structure	• Lower efficiency than PMSM • Requires complex inverter circuit • Control of motor is difficult	• Tesla Model X (BEV) • Toyota RAV4 (BEV) • Tesla Model S (BEV)
BLDCM	• Wide speed range • High efficiency • Compact structure • Large output torque	• Small constant power range • High cost due to PMs • Larger ripple than PMSM	• Honda civic hybrid (HEV) • Toyota Prius 2005 (HEV) • Smart Fortwo ED (BEV)
PMSM	• Wide speed range • High efficiency • Compact structure • Large output torque • Large power density • No rotor loss	• High cost due to PMs	• Soul EV (BEV) • BMW i3 (BEV) • Nissan Leaf (BEV)
SRM	• Simple and robust structure • Low cost • Wide speed range • Relatively high efficiency	• Large ripples • Much noise • Lower efficiency than PM machines • Complex control schemes	• Holden Commodore (BEV) • Chloride Lucas (HEV)

Errors, depending on their level of accumulation or severity disturb the motor's normal operation, producing several unwanted symptoms like unbalanced line currents, torque and speed pulsations, decreased efficiency, excessive heating and increased losses. As a result of

the increase of PMSMs in safety-critical applications such as EV motor drives, detection, identification and isolation of errors or deviations at their incipient stages is crucial. Undetected deviations from acceptable performance norms can lead to high substitution costs or possibly entire system failure. Hence the establishment of monitoring systems plays a huge role in detecting and diagnosing flaws within drive systems. Monitoring errors or abnormal behaviours of the PMSM drivetrain involves surveilling of motor-related operating parameters such as current, voltage, flux, speed, temperature, vibration, noise, partial discharge and the use of the correct strategy to evaluate the current operating state of the motor/machine. If the motor deviates from acceptable operational limits, it is necessary to further figure out the type of anomaly, location, severity and development pattern [34]. These deviations from normal operation can seriously affect the reliability and safety of the motor operation and can lead to high torque ripple generation, low efficiency and other grave safety-related problems if intervention (timely diagnosis and remedial measures) is not taken.

In a healthy machine it is expected that the center of the stator (c_s), the center of the rotor (c_r) and the center of rotation (c_ω) all align or coincide. The misalignment of the geometric centers of the stator and the rotor due to manufacturing imperfections lead to eccentricity errors which rank as some of the major root cause of PMSM problems. This phenomenon gives rise to the asymmetry of air-gap length, resulting in the Unbalance Magnetic Pull (UMP) between the stator and rotor. The UMP may further cause vibrations, noise and mismatch in phase currents [35]. Generally, up to 10% eccentricity is permissible. When eccentricity becomes significant it can cause rotor-to-stator rub and ultimately damage the rotor and stator winding [36], [37]. Electric machine errors emanating from eccentricity can be categorized as Static eccentricity (SE), Dynamic eccentricity (DE) and Mixed eccentricity (ME). In SE, both centers of the stator and rotor do not coincide. In this case, the position of the minimal radial air gap length is fixed in space. SE may be caused by the inaccurate position of the stator or rotor during the commissioning stage or simply by the stator-core ovality. Inherently, a small degree of SE tends to exist even in newly manufactured machines due to unavoidable manufacturing errors. DE occurs when the center of the rotor rotates around the center of the stator. In other words, in DE, it is the center of the rotor that is shifted from the center of rotation. This deviation may be caused by several factors such as bearing wear or misalignment, bent rotor shaft, mechanical resonance at critical speed [38]. Both rotor and stator centers are shifted from the center of rotation in the ME case. Stator current based approaches are some of the most widely utilized

strategies employed for detecting the eccentricity errors shown in Fig. 2-2. The analysis for the sources of error within the PMSMs is applicable to the other kinds of electric machines.

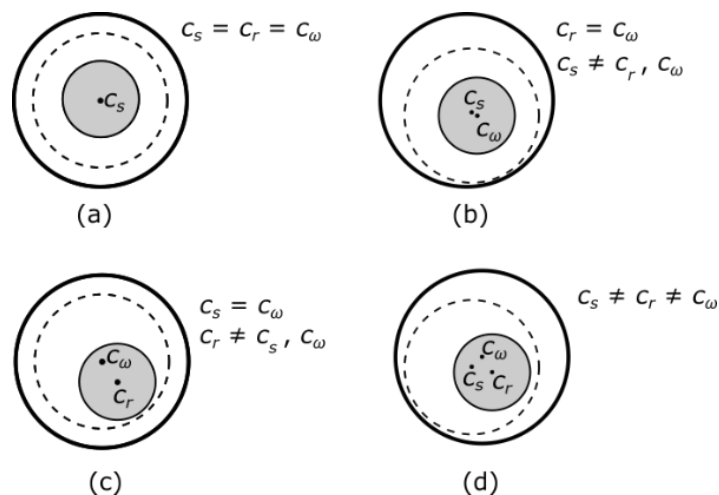


Fig. 2-2. Typical PMSM exhibiting different types of eccentricity. (a) healthy case. (b) SE. (c) DE. (d) ME.

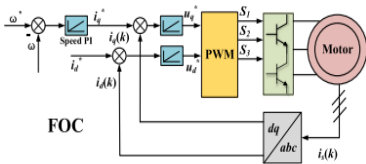
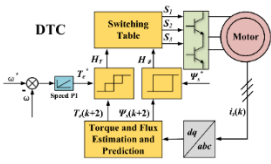
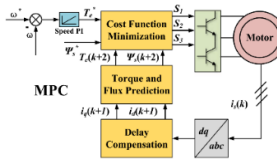
2.1.3 Control Strategies for Electric Machines

For satisfactory as well as energy-efficient operation of a typical electric drive system, control strategy plays a crucial role. Field-Oriented Control (FOC) and Direct Torque Control (DTC) are two of the most widely used control strategies for electric machines. These control methods are different in their operating principles, but their objectives are the same. They both aim to effectively control the motor torque and flux to force the motor to accurately track the speed and torque references regardless of the machine and load parameter variation. Essentially for FOC, the stator current space vector is decomposed into flux-forming and torque-forming segments by appropriate coordinate transformation. Each component is then controlled individually by a linear PID controller. FOC methods attempt to maximize torque production and minimize magnetization. The algorithm provides excellent steady-state performance and high control accuracy. For the DTC scheme, the basic idea is that the existing errors in torque and flux can be used directly to drive the inverter without any intermediate current control loops or coordinate transformation. Flux and torque controllers are hysteresis types and their outputs are used to determine which of the possible inverter states should be applied to the machine terminals so that the errors in the flux and torque remain within their prescribed hysteresis bands [39]. DTC possesses several advantages such as elimination of coordinate

transformation, lesser parameter dependence and faster dynamic response. However, its major drawback is its relatively high current and torque ripple due to the presence of hysteresis comparators together with the limited number of available voltage vectors [40].

Model Predictive Control (MPC) on the other hand is an attractive alternative to conventional PI control due to its simplicity, fast dynamic response, robustness and the ease with which it handles nonlinear constraints [41]. Based on the internal model of the system, MPC predicts the future behaviour of controlled variables such as current, torque and stator flux. By minimizing the error between the reference value and the predicted value, the best voltage vector can be obtained. A major drawback of MPC is that it needs an accurate model of the system, and this is usually not a simple task in highly dynamic systems. However, in recent years the modelling of complex electrical systems has been greatly improved and this challenge can be resolved. Table 2-2 summarizes the essential features of some of the most popular control algorithms used in motor drives.

TABLE 2-2 Comparison of Conventional Control Strategies for EVs

Aspect	FOC	DTC	MPC
Pictorial depiction			
Structure	- One speed PI and two current PI controllers - Space vector modulation required	- One speed PI and two hysteresis controllers - Inverter Switching table required	- One speed PI and predictive controller - Cost function is required for optimization
Merit	- Fixed switching frequency - Low computation burden - Low THD - Low Torque ripple	- Low switching frequency - Low computation burden - Fast transient response - Easy tune	- Lowest switching frequency - Easy to tune. - Fast transient response - Large current control bandwidth

Weakness	• High switching frequency • All parameters required except resistance. • Modulation required and difficult to tune. • Slow transient response • Small current control bandwidth	• High THD • All parameters required except resistance. • Small current control bandwidth • Normally combined with other strategies	• High computation burden • Sensitive to parameters • Low robustness • Sensitive to small-inductance motors
Applications	• Existing application in EVs • Low noise	• Widely applied in high-power EVs	• Future trend for direct-drive propulsion system

2.2 Errors in the Electric Powertrain

2.2.1 Three-phase Power Inverter

The inverter, which represents one of the most used circuit configurations utilized for speed control in many three phase machine applications is a key component within any EV. Its main objective is to produce an alternating current (AC) output waveform from a direct current (DC) supply. A fixed DC input voltage is given to the inverter and a controlled AC output voltage is obtained through the adjustment of the on and off periods of its interior components (switches). Being such a vital component, it controls the electric motor and analogous to the engine management system within gasoline cars, it determines the EV's driving behaviour. In instances when the brake pedals of the vehicle are engaged and the motor operates as a generator, the inverter acts as a rectifier and returns energy to the battery. High power Insulated Gate Bipolar Transistors (IGBTs) or Silicon Carbide (SiC) Metal Oxide Semiconductor Field Effect Transistors (MOSFETs) represent the key constituents of the power inverter which control the flow of energy to the motor to initiate motion. Both the top and bottom switch of the inverter leg are controlled via the microcontroller and gate drivers. As the motor operates, the current, position and voltage signals are sensed and fed back to the controller to change the inverter's modulation. An efficient modulation algorithm, swift feedback and precisely sensed signals are necessary for effective motoring to take place. Errors in the power inverter could occur due to inverter intermittent misfiring because of defects in control circuit elements or electromagnetic interference which results in gate-drive malfunctions [42].

To guarantee that the top and bottom switching devices never conduct simultaneously, a small time-

delay is added to the gate signal of the turning on device. This delay is termed dead-time. In other literature, it is referred to as blanking time or delay time. The dead-time is inserted when both the upper and lower switch within the leg of the inverter is switched off [43]. Its value depends on the type and power rating of devices utilized to construct the power inverter circuit [44], [45], [46]. For power semiconductor devices with notably high switching speeds, a proper dead-time must be selected to ensure correct and safe operation of the inverter. Since the two active switching devices are in off mode during the dead-time, either the top or bottom diode conducts depending on the direction of load current flow. Hence an error could be generated in the output voltage depending on the direction of this load current. Even though the error in voltage is only for a short duration, cumulatively the impact of this could be significant especially when carrier frequency is high [47]. The insertion of dead-time assures safe operation, nevertheless, it causes major output voltage distortion, which further leads to an increase in current harmonics and deterioration in control performance [43], [48], [49], [50]. Inverters have other non-ideal factors such as voltage drops across the switches during on-states, switching delays, parasitic output capacitances of switches and propagation delays in gate drive circuits. These factors also serve as sources of output voltage distortion [51], [52], [53], [54].

2.2.2 Analysis of Dead-time Effects

A typical configuration of a Voltage Source Inverter (VSI) interfaced with a PMSM load is depicted in Fig. 2-3, IGBTs are utilized as switching devices. The pole voltages (voltage at the midpoint of a leg measured with respect to the midpoint of the DC bus are referred to as V_{AO} , V_{BO} , V_{CO}). If the three phase VSI is modulated using sine triangle PWM strategy, then the three sinusoidal modulating waves can be compared with high frequency triangular carrier waves and gating pulses can subsequently be generated for the six switches of the VSI. In the comparison, if the modulating signal is greater than the carrier wave, the top device will be on, otherwise, the bottom switch will be active.

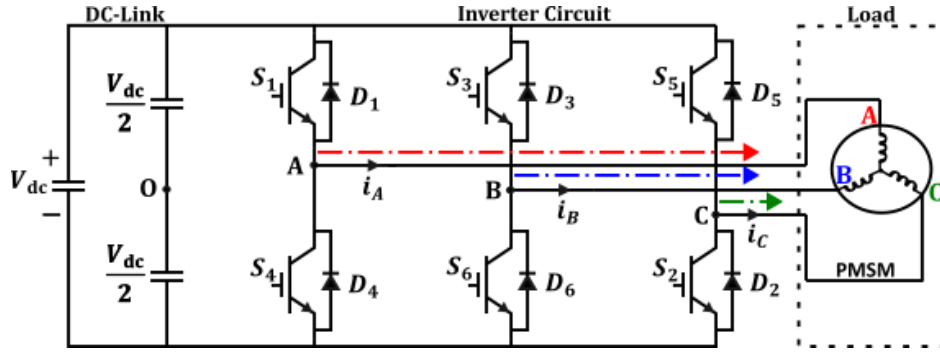


Fig. 2-3. Three-phase PWM Inverter with PMSM Load.

Depending on whether the load current is positive or negative, the pole voltage transition will take on different patterns and an error will always ensue due to insertion of the blanking time. The load current direction is considered positive when its direction is towards the load. By referring to Fig. 2-4 (a), if the gating pulse of S_1 is high, it will conduct and current will flow from its collector to the emitter, then finally to the load. However, if the gating pulse to S_1 is low, it will not turn on. The only way for the current to continue flowing positively to the load is through the feedback diode D_4 . On the other hand, the load current is considered negative when its direction is towards the inverter. Consider the instance, when the gating pulse of S_4 is high as depicted in Fig. 2-4 (b), it will conduct and current will flow through it conventionally.

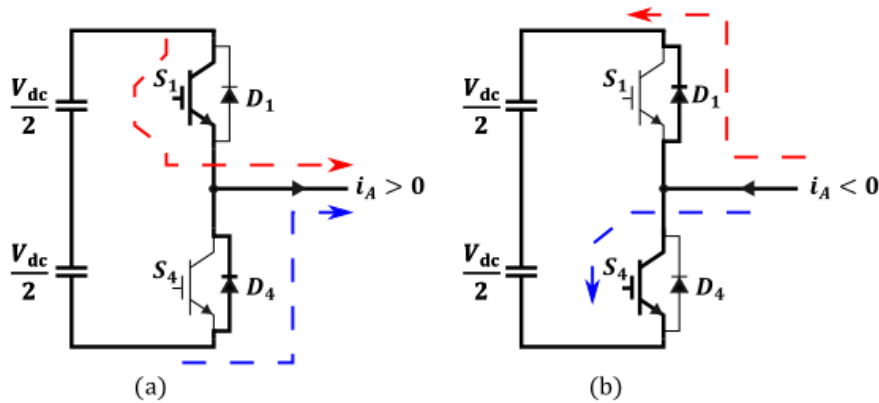


Fig. 2-4. Impact of current flow on pole voltage transition for (a) positive direction of current flow. (b) negative direction of current flow.

However, if its gating pulse becomes low, even though the gating pulse of S_1 will be high at this instant, it will not be able to conduct due to the direction of the load current (i_A). Since current can only flow through the switch from collector to emitter, the only available path for

the load current to flow is through feedback diode D_1 . Hence in summary it can be observed that whenever the load current is positive, either top switch S_1 or bottom diode D_4 will be turned on. Likewise, whenever the load current is negative, either top diode D_1 or bottom switch S_4 will be on.

The gating pulses (ideal and actual) as well as pole voltages (actual and ideal) are depicted in Fig. 2-5 when the load current is positive. By considering Fig. 2-5 (e) for initial analysis, when S_1 is on and the load current is positive, the pole voltage in phase leg A (V_{AO}) equals half of the DC bus voltage $\left(+\frac{V_{dc}}{2}\right)$. Similarly, when D_4 is on and the current flow is towards the load, V_{AO} emerges as negative of half the DC bus voltage $\left(-\frac{V_{dc}}{2}\right)$. From Fig. 2-5 (c), by inserting the blanking time the rising edge of both actual gating signals are delayed by time, t_d . The actual pole voltage pattern is generated based on the behavior of actual gating signals. By referring to Fig. 2-4 (a) and Fig. 2-5 (c) when S_{1D} (actual gating pulse of S_1) is low, the complementary switch S_{4D} (actual gating pulse of S_4) happens to be high however since i_A is positive, it cannot flow through the bottom switch hence the feedback diode D_4 will conduct at a pole voltage of $\left(-\frac{V_{dc}}{2}\right)$ instantaneously. During the deadtime, the gating pulses of both S_{1D} and S_{4D} remain low hence it can be seen from Fig. 2-5 (d) that the diode continues to conduct during the delay to keep i_A in the positive direction, maintaining V_{AO} at $\left(-\frac{V_{dc}}{2}\right)$ in the process. Subsequently, the gating pulse of S_{1D} is made high and the current flows in the usual fashion to the load and conducts at $\left(+\frac{V_{dc}}{2}\right)$ pole voltage. When the gating signal of S_1 is made low, it immediately turns off.

The rising gating pulse of the bottom switch is delayed by the dead-time. At this stage, pulses happen to be low for both switches, however since i_A remains positive, the only device which will conduct to maintain the current in this direction is D_4 at a pole voltage of $\left(-\frac{V_{dc}}{2}\right)$. A comparison of Fig. 2-5 (d) with (e) depicts that the introduction of the blanking time changes the appearance of the actual pole voltage pulse. A useful observation can be made in Fig. 2-5 (d), again in comparison to its ideal counterpart. It can be noticed that the transition pole voltage is delayed by the dead-time if the incoming device is a transistor, whereas it does not get delayed if the incoming device is a diode. The difference between the actual and the ideal pole voltages results in an error pole voltage of $-V_{dc}$ (Fig. 2-5 (f)). Hence in one carrier cycle, there

is always one error voltage pulse in the pole voltage. The pattern will repeat itself in subsequent carrier cycles.

A similar analysis like was done previously is carried out in examining the pole voltage transitions when the load current flows towards the inverter. The ideal and actual pole voltages together with the gating pulses (ideal and non-ideal versions) are depicted in Fig. 2-6. By comparing Fig. 2-6 (d) and (e), just as was done when i_A was positive, it can be observed from the generation of the actual pole voltage pattern that when the transition is from diode to transistor, the transitional pole voltage is delayed by t_d , however when the transition is from transistor to diode, there is no delay. Therefore, in one carrier cycle when the load current is negative, an error voltage pulse of height V_{dc} and width equal to t_d is obtained.

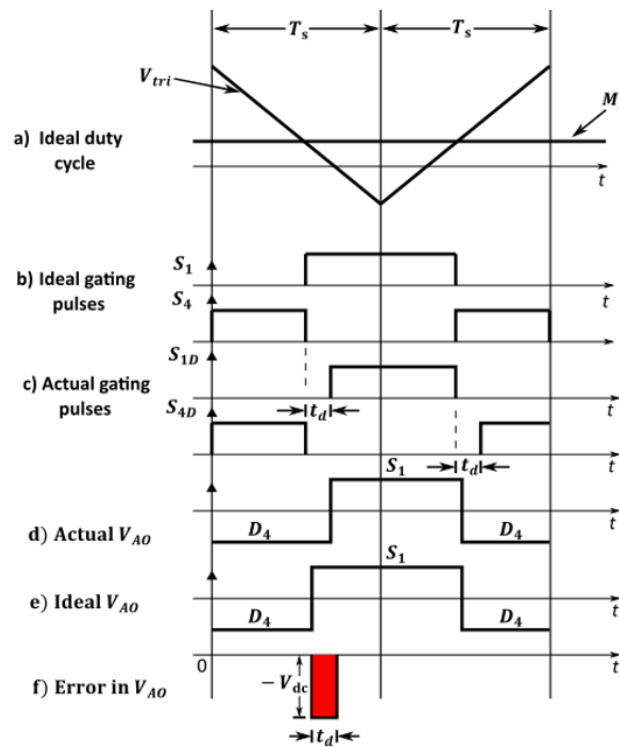


Fig. 2-5. Pole voltage transitions for positive load current.

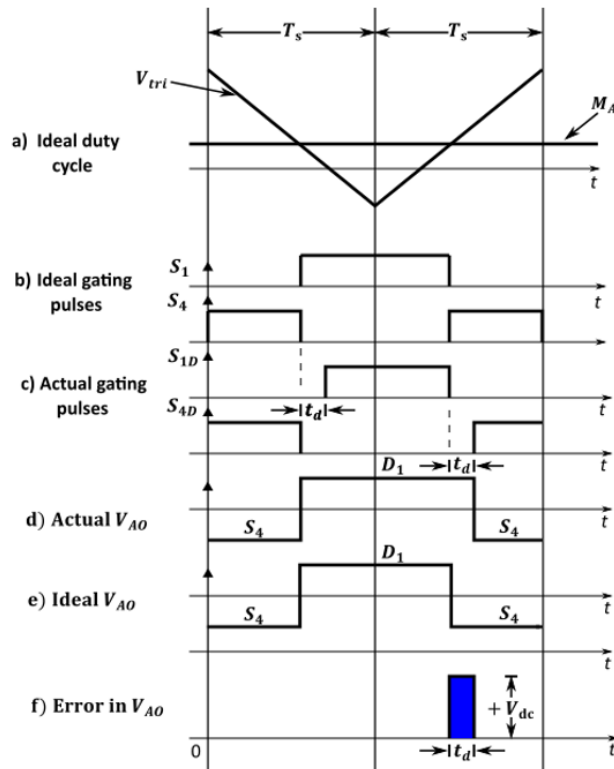


Fig. 2-6. Pole voltage transitions for negative load current.

Fig. 2-7 depicts the generation of error voltage pulses over the positive and negative cycles of the fundamental load current. In the positive half cycle of the load current, negative pulses exist and vice versa. Since the pulses have the same height and width in every carrier cycle, they will have the same average value in all carrier cycles hence a square wave can be utilized for approximation.

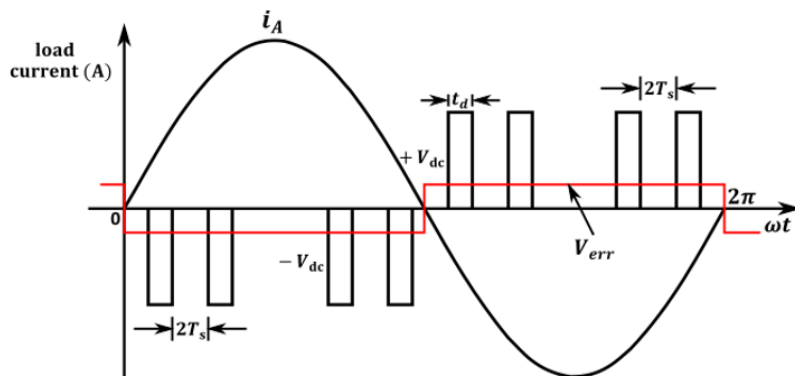


Fig. 2-7. Error voltage pulses over a cycle of fundamental load current.

The average error pole voltage is given by

$$V_{err} = \frac{V_{dc} * t_d}{2T_s} \quad (2-1)$$

where V_{err} represents the average error pole voltage, V_{dc} is the dc source voltage, t_d is the dead-time inserted and T_s represents the switching period.

By applying the Fourier series to the square wave voltage, it can be decomposed into fundamental component (a small portion of it) and low frequency portions (5th, 7th, 11th and 13th) as well as the switching frequency components (f_s , $2f_s$). The troublesome components are the fundamental and low frequency constituents. The output voltage should ideally follow the desired sinusoidal waveform, but because of the introduction of the dead-time, there is a small gap where the voltage drops to zero. This gap, or zero-voltage region introduces an average error voltage into the inverter output voltage waveform. The average error pole voltage is essentially an average of the voltage during the dead-time. Since it is not part of the desired sinusoidal waveform, it can lead to the distortion of the output voltage. $V_{AO}(Av)$, the ideal average pole voltage, represents a scaled version of M_A . For the dead-time analysis for the zero-power factor instance shown in Fig. 2-8 (a), i_A lags $V_{AO}(Av)$ by 90°. When i_A is in its negative cycle the average error pole voltage is positive and vice-versa. Hence the actual pole voltage is the sum of $V_{AO}(Av)$ and V_{err} . The actual pole voltage is no longer purely sinusoidal, as its distorted significantly.

In the lagging power factor case, i_A lags $V_{AO}(Av)$ by some angle below 90° as depicted in Fig. 2-8 (b). Again, the actual pole voltage is not purely sinusoidal due to distortion introduced by the dead-time. Fig. 2-8 (c) portrays the unity power factor scenario, where i_A is in phase with $V_{AO}(Av)$. To obtain the actual pole voltage, $V_{AO}(Av)$ is added to V_{err} in all three scenarios and additionally the square wave is out of phase with the fundamental current in all three power factor scenarios. The average pole voltage depends on the direction of the fundamental current.

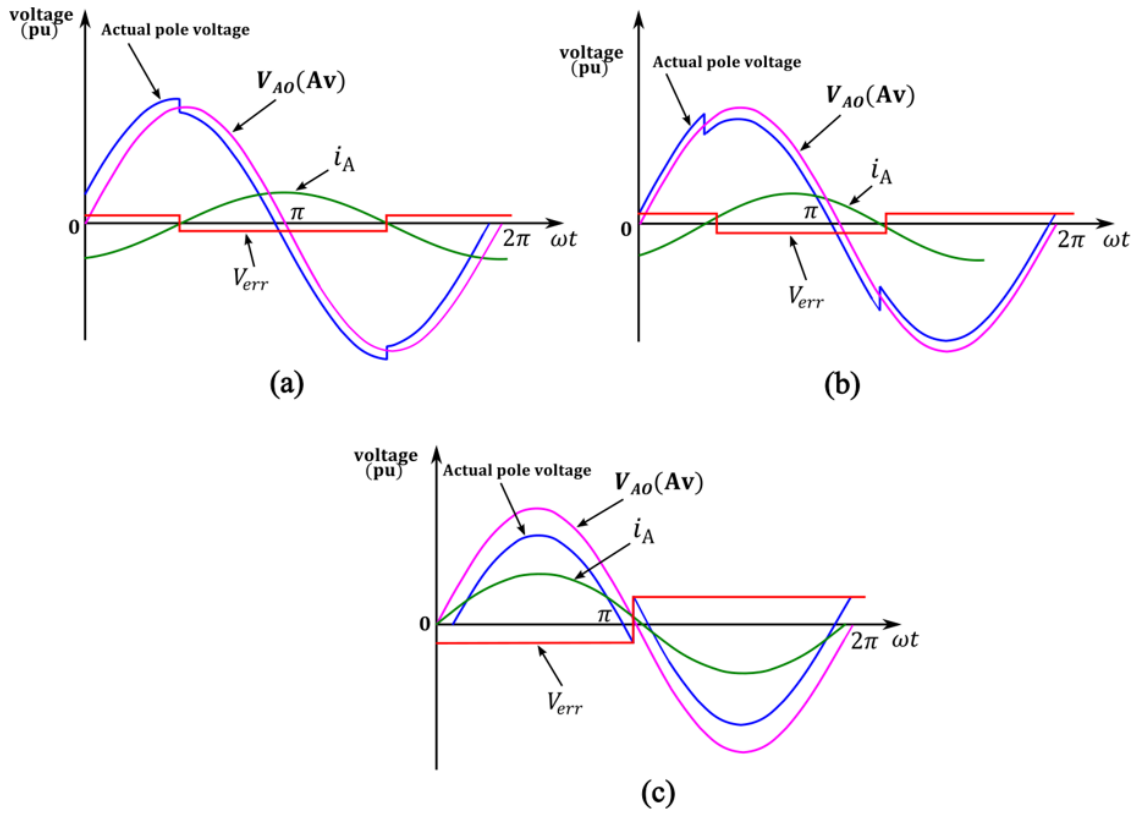


Fig. 2-8. Dead-time error for sine-triangle PWM technique for (a) zero power factor scenario. (b) lagging power factor scenario. (c) unity power factor scenario.

Over the past few decades, substantial research has been carried out for VSI nonlinearity compensation in three phase motor drives. Numerous dead-time compensation strategies exist in literature today. The conventional dead-time compensation methods can be classified into two major categories. The first group, classified as pulse-based compensation strategies detect voltage error introduced by the dead-time and then compensates for it in the next PWM cycle. The dependence on the current polarity is crucial in the pulse-based methods. In [50], [55], [56], [57], [58] and [59] current polarity detection is made possible with direct analog-to-digital (A/D) samples.

However, these approaches are imprecise and exhibit inefficiency at detecting current polarity especially around the zero-crossing region. Consequently, if the polarity information suffers from imprecision, the distortion will worsen after compensation. In [60], polarity detection precision is enhanced through feedback circuits to measure inverter output voltages and Kalman filters to perform reconstruction of fundamental phase currents. A special detection circuit is used in [61] to detect the current polarity, with the VSI being regulated by a Field Programmable Gate Array

(FPGA). These approaches require extra circuits which increase the overall cost and hardware complexities. Additionally, majority of these methods are not completely accurate under entire operating conditions since the switching device parameters such as turn-on / off times, saturation voltage and diode forward voltage change depending on operating conditions [52]. Hence precise compensation cannot be guaranteed as the operation condition varies. All pulse-based techniques correct the output voltage magnitude accurately, but possess a phase delay [62]. Consequently, phase lag elimination methods have been proposed in [63], [64], [65].

The second category comprises compensation strategies in which the voltage error caused by the dead-time is reduced by alteration of a reference voltage. In these solutions, a compensating voltage is appended to the reference voltage [66], [67]. These compensation techniques can be called average value compensation strategies or volt-second compensation schemes because they utilize the average value of a compensating voltage [68], [69]. Even though the implementation of these methods are straightforward, they require precise current polarity and compensation time [53], [55], [70]. Majority of the schemes use current sensors to detect the polarity of the current [71]. However, due to the zero drift and the noise of current sensors, it is a challenge to judge the current polarity accurately especially when the current crosses zero. An approach based on voltage sampling strategy to obtain the current polarity is proposed in [72], nevertheless it leads to disappointing results due to the fluctuation of neutral point (NP) potential when the methods are applied to three level inverters. In [52] an approach for instantaneous back calculation of current phase angle with a single current sensor is proposed, while the introduced time delay and phase error cannot be ignored. In [61], [73], high precision current polarity judgement is realized by detecting which antiparallel diode conducts in a phase leg. However, the necessary hardware circuit is relatively complicated. Although these strategies achieve good performance, they accrue cost due to the use of extra circuits. By comparing the two compensation schemes, the average value compensation scheme is easy to achieve albeit exhibiting a slow compensation action. The other category provides more precise and faster compensation but increases the overhead on the processor [44], [54].

To bypass the problems of current polarity detection, an alternative approach based on disturbance observation is studied in [74], [75], [76], [77] where the total voltage error is estimated through observers. These methods require accurate motor parameters and do not need current polarity detection and offline experimental measurements. It requires lots of experience and effort to acquire the adequate value of tunable parameters [78]. Moreover, only systems installed with speed sensors

and at least two current sensors can adopt this method, hence application is limited [72]. In references [78], [79], [80] distance observers are utilized to calculate the voltage errors caused by VSI nonlinearity in the synchronous d-q reference frame. The voltage errors are subsequently compensated by adjusting the voltage references through a feedforward loop. Though the approach leads to successful results, the estimation errors can deteriorate the compensation performance due to motor parameter changes. In [81], the predictive controller is utilized to enlarge the control system's robustness against parameter changes and the parameters within the observer can adaptively be adjusted, nevertheless it requires information on the output voltage feedback.

In the PWM inverter, voltage distortion due to the dead-time effects produce sixth current harmonics in the dq-axis synchronous reference frame [82]. Based on this theory, numerous compensation strategies based on monitoring the current harmonics introduced by dead-time effects have been proposed. For instance in reference [43], a novel adaptive filter based compensation scheme is utilized to suppress the dead-time effect by decreasing the 6th harmonic in the synchronous reference frame. The outstanding feature of the proposed strategy is the utilization of the positive and negative sequence components of 6th harmonics from dq-axis currents. By using the sequence information of the 6th harmonics, the compensated voltage can be estimated directly utilizing the voltage equation, hence bypassing the phase lag of proportional integral (PI) current regulators witnessed in reference [82]. The proposed method is superior again because in comparison with [83], it requires no additional information besides the rotor speed and dq-axis currents. Compared to the average- based and disturbance observer-based methods, the proposed strategy is robust to motor parameter changes since a feedback path with variable gains is designed based on the magnitudes of the sequence harmonics [43].

Since the dead-time insertion introduces low order harmonics [84], it is possible to reduce these harmonics through the utilization of Multiple Resonant Controllers (RSCs). Even though the RSCs can compensate for the low order harmonics with efficacy, they have a tendency to trigger system resonance in instances where higher order harmonics (for example 11th or 13th order harmonics) are compensated in order to fully alleviate the dead-time [85]. A very promising solution for the harmonic suppression is to utilize a Repetitive Controller (RC) premised on the internal model principle [86]. This can suppress all harmonics (dead-time inspired harmonics included) without having to worry about resonance issues, so long as a good design algorithm is adhered to. As such, a scheme is proposed in [85] in which an RC is plugged into a proportional resonant based fundamental controller to get rid of dead-time effects in grid-connected PWM converters. In

comparison with the conventional dead-time compensation approaches, the RC compensates the dead-time harmonics as well as other low-order distortions with efficacy. Even though this strategy is effective in significantly minimizing the low order harmonics, it does not consider other dead-time related high order harmonics. To remedy this flaw, reference [87] proposes a dead-time compensation scheme based on a revised RC (RRC) which is installed in conjunction with current PI controllers. Unlike the other RCs, the proposed RRC uses Finite Impulse Response (FIR) moving average filter with a simple structure and is easier to implement utilizing commercial microcontrollers. It guarantees the tracking precision and its parameters can be kept fixed for myriad operating conditions [87]. Due to the nature of repetitive control, RRC has better robustness against motor parameter changes compared to disturbance observer-based methods. To add to this, the scheme does not only minimize the 6th harmonics as in many other compensation strategies but also deals with its multiples simultaneously.

2.3 Sensors for Closed-loop Control of Drive System

For control purposes, the EV drive system is normally embedded with a feedback circuit which comprises various kinds of sensors utilized to extract signals of three phase stator currents, position and motor speed. Fig. 2-9 shows some of the major components utilized within the feedback and main circuit of the closed-loop system for effective control. All these essential elements operate in synergy for efficient electromobility. The performance of the system can be measured by the health of sensors used in the control process. In other words, the reliability and stability of the electric drivetrain is tied to the efficient operation of the different kinds of sensors.

However, due to exposure to excessively harsh environments, gradual ageing of devices and other external influences, the sensors at some point in their lifetime are bound to malfunction resulting in deviations in the feedback signals of the control system which ultimately affects the control performance and subjects the sensor precision to considerable degradation. The effect of this is the transmission of corrupted signals. Once a sensor has been buffeted by errors, it might end up not giving any information at all and if it happens to provide any, it might not correspond to the true value of the measured variable. In some not so serious error-prone scenarios, the sensor could deliver a signal at least adequate to the true value of the measured variable. Errors, in isolation or accumulation could lead to sensor failures and result in the collapse of the entire powertrain system, possibly resulting in serious road accidents. An

effective means to enhance the reliability of the drivetrain is to identify errors at incipient stages and initiate a structured reaction to prevent the eventual malfunction of the whole drivetrain system. However, the complexity of EV powertrains makes this a challenging feat. Besides this, how much each sensor affects the reliability of the whole system as well as measures to detect which of them exhibit the most vulnerabilities within the entire powertrain can be difficult to capture. Reference [88] puts forth a favourable approach to dealing with the problem of sensor accuracy uncertainty caused by aging and exposure to harsh conditions. It proposes a strategy that utilizes a detection voltage injection (DV-injection) approach for the mutual calibration of sensors. Out of the various EV drivetrain sensors, the position, current and voltage sensors play highly influential roles to contribute to seamless propulsion.

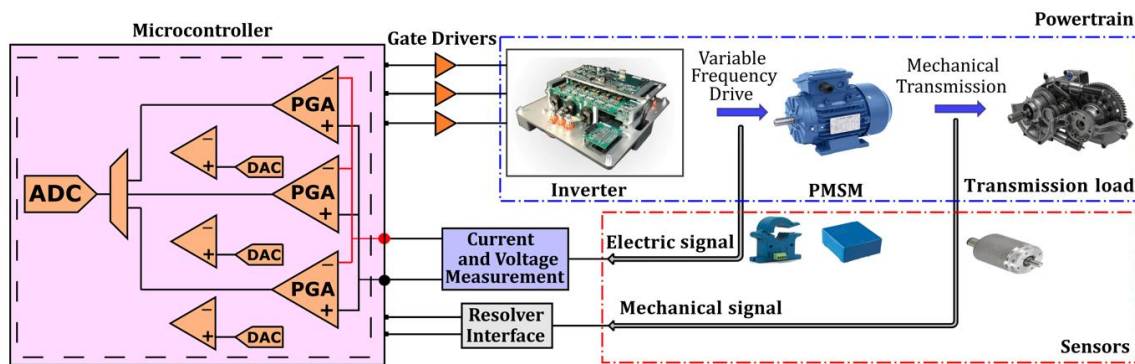


Fig. 2-9. Sensors used in the closed-loop control of the drivetrain.

2.3.1 Analysis of Current Sensor Measurement Errors

Typically, high-precision current sensors are installed to provide accurate current feedback signals which are crucial for normal and efficient operation of the drive. These sensors are not flawless and could witness varying levels of precision degradation due to : errors of the current sensor itself, parameter error in the signal processing circuits and discrete errors within the digital signal processor [89]. The two main types of current sensor errors are offset and scaling errors [90], which cause periodic speed ripples with one and two times the fundamental current frequency respectively [91]. The offset error within a measurement refers to a superimposition of a value onto the actual measured current. It is typically caused by drift phenomena or residual current of current sensors or offset of operational amplifiers and Analog-to-Digital Converters (ADCs) in the measuring circuits. The scaling errors on the other hand refer to nonideal scaling gain for the phase current which generally results from disparate gains of the two current

measurement channels, including operational amplifiers, current sensors and imprecision of passive elements within the measuring circuits [92].

Offset on current feedback is one of the dominating sources of torque ripple in a motor drive and it is desirable to minimize it as much as possible. Generally speaking, there are two types of offset errors on current feedback [93]. Firstly, there is the static offset which tends to be present at any point in time and at any temperature. A common technique to minimize the impact of static offset is to perform offset calibration that can be done either at the time of manufacture or at instances when the motor current is zero. With this approach, static offset becomes constrained. Secondly, there is the offset drift that is a function of parameters such as temperature and time. Offset drift is more complicated to deal with. As this is a slow drift that usually happens while the motor is operating, it is difficult to perform online calibration and stopping the motor is usually not an option. Some online calibration techniques based on observers have been suggested, but the observers rely on models of the motor's electrical and mechanical system. For online estimation to be effective, exact knowledge of the motor parameters are required and that is extremely difficult if not impossible. The most effective mitigation of offset drift is to utilize a three-channel current measurement feedback system. Assuming the channels use the same type of components, the drift channels are likely to be similar. In this case, the offsets will cancel out and will result in zero torque ripple [93].

The current measurement errors emanating from the offset and scaling error degrade torque control performance. They are responsible for causing both transient and steady-state error on the stator currents, both of which could adversely impact torque performance (through the introduction of ripples). Typical components which come together to enable effective current measurement include noise filter circuits, ADCs, and Hall-effect current sensors. These devices which collaborate to provide accurate measurements are prone to varying forms of imperfections due to temperature drift, noise and ageing. In such situations, the reliability and performance of the drive system become open to compromise and will most likely experience speed fluctuations, torque ripple and mismatched phase currents. Undetected measurement errors could worsen over time hence periodic compensation schemes are crucial [92]. Even though the best measurement paraphernalia could be put in place to ensure current sensors work under the most conducive conditions, this does not guarantee obtaining impeccable measurement accuracy [91], [94].

A lot of research has been conducted on analysing and compensating for current measurement

errors. In [95], [96] the filters (low-pass and bandpass) which are used to evaluate the direct current (DC) output voltage ripples are used to filter out the offset and scaling errors. In [92], the impact of the current error on the phase current and output voltage of a current controller is carried out. The compensation is carried out through the manipulation of the voltage error. The proposed strategy depends on the commanded voltage reference of the current controller. The paper describes with clarity how the voltage error resulting from the offset error and scaling gain difference could be separately compensated for, however, it does not provide sufficient information as to how the voltage error emanating from the average scaling error could be separated from the parameter error. In [91], [97], [98], the error signal which is obtained from the difference between the reference and feedback values of the current controller is used to approximate the current measurement errors. In [99] an upgraded current control design made out of a proportional resonant controller and a repetitive controller is utilized in the synchronous d-q reference frame to eradicate the DC and harmonic currents caused by voltage measurement errors and voltage distortion in a three-phase grid-connected inverter.

The existence of parasitic torque pulsations poses a real threat to the effectiveness of PMSM vector control. They occur primarily due to errors in current measurements and the changing magnetic reluctance of the air gap. In [100], the impact of these parasitic torque pulsations, which by nature, change periodically is analysed. An iterative learning control (ILC) is proposed as the most suitable choice to minimize the torque ripple. The approach takes advantage of the periodic nature of the torque ripple to maximally counter them [100]. In [101], a strategy is introduced for compensating current measurement gain errors through the injection of high frequency voltage. This method tends to complicate torque ripple issues and acoustic noise in certain applications [102]. Reference [103] studied the impact of current sensor gain deviation utilizing the complex vector current sensor gain model under myriad sensing scenarios and suggested a compensation strategy. The analysis carried out discovered that if two current sensors are used, both the negative and positive sequence current components are affected by measurement gain errors, whereas if three current sensors are used, only the negative sequence current tends to be affected by a current measurement gain error. However, the compensation strategy does not come up with an explicit solution to handle the current sensor gain deviation errors. Analysis conducted in [91], [104], [105] mainly compensated for the current measurement error by utilizing the commanded voltage reference of the current controller. The compensation methods in these instances were hampered by operating speed

conditions though. [106] laid emphasis on the detection of current sensor faults in IPMSMs, utilizing the services of a state observer to supply any missing information in the case of faults, yet still keeping the integrity of the vector control strategy intact. The approach presented is geared towards a scenario of complete current sensor break down and barely throws any light on specific compensation techniques to tackle either scaling or offset errors.

2.3.2 Current Sensors' Placement and Their Contribution to Error

The information concerning the three phase output currents of an inverter is of great relevance. Many PMSM-based applications require these three-phase current information to be accurate to effectively carry out FOC. Typically, two or three Hall-effect current sensors mounted in the inverter output leads connected to the three-phase load are utilized to provide phase current information. The use of multiple current sensors tends to increase the cost, volume and overall drive system complexity. To add to this, mismatches in the output characteristics of multiple current sensors lead to imbalances in phase currents and torque ripple generation [107]. Consequently, an alternative approach which utilizes a stand-alone DC-link current sensor to reconstruct the phase currents successively has become popular. Fig. 2-10 pictorially depicts how current sampling is achieved through the utilization of a single DC-link current sensor and multiple phase current sensors. Based on the active voltage vector applied to the machine(load), the DC-link current is sampled at distinct time instances within a switching period.

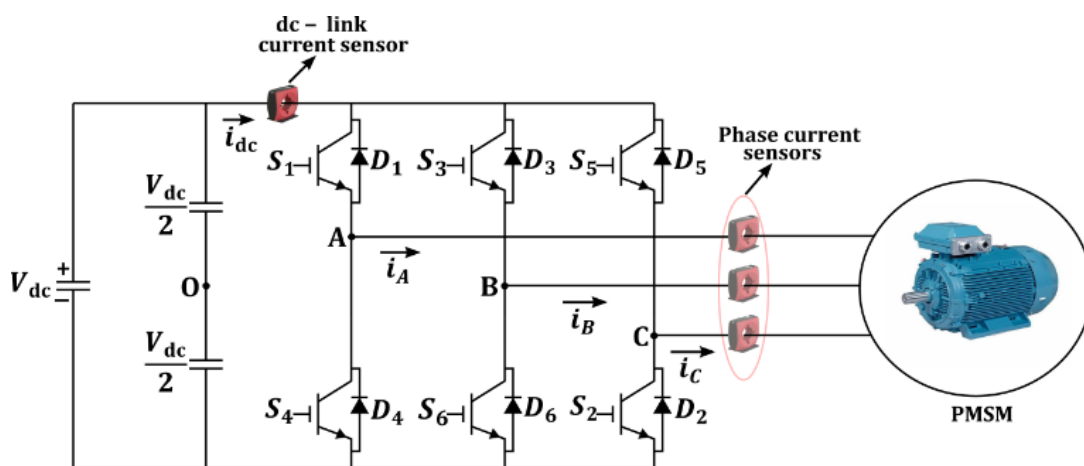


Fig. 2-10. Current sampling with stand-alone DC-link current sensor and multiple phase current sensors.

Table 2-3 shows the sampled currents based on the active voltage vector applied at any instant.

TABLE 2-3 Relationship between DC-link current and Applied Voltage vectors

V_i	V_0	V_1	V_2	V_3	V_4	V_5	V_6	V_7
i_{dc}	0	$+i_A$	$-i_C$	$+i_B$	$-i_A$	$+i_C$	$-i_B$	0

Within any switching period, two distinct active vectors are applied, therefore two-phase currents can be sampled from the DC-link current, and the other phase current is estimated via the equation below

$$i_A + i_B + i_C = 0 \quad (2-2)$$

where the load phase current is represented by $i_p, p \in \{a, b, c\}$.

In utilizing the single DC-link current sensor, a minimum time is needed to perform accurate DC-link current measurement when an active voltage vector is applied. This time is expressed as

$$T_{\min} = T_{\text{dead}} + T_{A/D} + T_{\text{sett}} \quad (2-3)$$

where T_{dead} represents the dead time introduced to prevent a short circuit within any of the three legs of the inverter, T_{sett} is the settling time required for current to become stable and $T_{A/D}$ represents the summation of the sampling time, t_{samp} and A/D conversion time, t_{conv} . However, with the single current sensor approach, the duration of the active voltage vector is not adequate to accurately measure the DC-link current during every single PWM switching. This leads to the introduction of reconstruction dead zones (known as immeasurable areas in other literature), where the current sampling and reconstruction technique become handicapped to perform. In other words, if the reference voltage happens to be present in the immeasurable area, it will not be possible to accurately detect the three phase currents since at least one of the active state vectors is not applied long enough to enable precise measurements. Fig. 2-11 shows areas where current reconstruction is established with ease and under constraint.

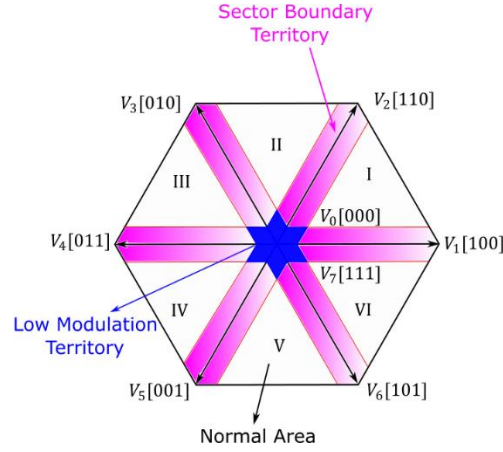


Fig. 2-11. Normal working areas and current reconstruction dead zones.

Within the sector boundary region, just one active voltage vector possesses adequate interval to measure and link the corresponding phase currents whereas it is virtually impossible to detect a phase current in the low modulation region since the applied voltage time of both active voltage vectors is shorter than T_{min} and due to the existence of zero voltage vectors.

In order to effectively constrict the current reconstruction dead zones, modified PWM strategies are introduced which include Measurement Vector Insertion Method (MVIM) [108], [109], [110], [111], [112] and Switching-state Phase Shift Method (SPSM) [113], [114], [115], [116], [117], [118], [119]. In [108], the MVIM is proposed to reconstruct the phase currents by utilizing the active voltage vectors that are applied momentarily only when its necessary during each fundamental frequency cycle. To minimize the effect of output current ripples and switching losses, the SPSM, which works on the principle of PWM pattern adjustment/modification is performed by applying phase shifts to the switching-state waveforms of the inverter [115]. To resolve the drawbacks associated with the reconstruction dead zone, in [118] a novel PWM compensation strategy which excludes the use of null vectors is proposed. By using the other available active voltage vectors to synthesize the null switching states, sufficient active switching states can be obtained when the current reconstruction zone is apportioned into six sectors and each sector subsequently put into tripartite sections utilizing distinct vector synthesis methods. Even though these modified PWM schemes can tune the PWM signals to ensure that the two-phase current can be sampled in each PWM period, the approach generates current ripples, extra switching losses and current harmonics [107].

Other approaches which are utilized to compensate for the reconstruction dead zone problem include the state observer methods [120], [121], [122], [123], [124]. In [120], a sinusoidal

curve-fitting observer which excludes load parameters is utilized to resolve this issue. By this scheme, the adopted observer is capable of generating stable three-phase feedback signals even momentarily by utilizing a combination of the firing signals and the DC-link current for corrective action. In [122] an upgraded Luenberger-style observer is merged with a space vector-based lookup table to reconstruct the motor line current. Even though the observer-based procedures can utilize the observer output current for line current reconstruction in times when measurement of the DC-link current is impossible, they have sensitivity issues as far as system parameter changes are concerned and also need complex control design. To bypass the complex algorithm as well as the rise of the switching times, the dual-positions-coupled sampling strategies are developed [125], [126], [127], [128]. In paper [126] a three-phase current reconstruction technique equipped with online offset compensation functionalities is proposed. The scheme measures a phase and branch current twice at the same time for a given switching period with a single current sensor. Subsequently, the current reconstruction method is applied to obtain the three-phase current information. The proposed procedure effectively samples the sensor output current regularly and shifts the location of the dead zone in close proximity to the boundary of the voltage vector space, instead of being close to the origin and borders of the various sectors. The newly defined zones do not have to deal with repeatedly having to encounter the dead zones. This makes it even more effective in low modulation index situations. Reference [127] proposes a novel vector sampling approach which can relocate the current reconstruction dead zones in the low modulation and sector boundary territories towards the outline of the space vector hexagon, keeping the PWM signal unmodified. The suggested methodology is then able to sample currents in two null vectors by arranging the single current sensor at a novel location.

In the use of a single DC-link current sensor, since the phase current is only sampled in active voltage vectors (basic vectors) or null state vectors (zero voltage vectors) it becomes inevitable to have to deal with the reconstruction dead zone dilemma [107]. Therefore to solve this common problem associated with current reconstruction in most literature, [107] puts forward a multiple-positions-coupled sampling strategy. The scheme enables two independent equations of the stator current to be extracted by sampling the single DC-link current sensor twice in both active vector states and null vector states. The phase current reconstruction is precisely achieved by solving these two equations, in which case the current reconstruction dead zone is repositioned toward the six corner edges of the space vector hexagon.

2.3.3 Position-Sensor Approach

In the field of motor drives, accurate, high resolution rotor position information and knowledge of motor currents are needed to correctly achieve optimal vector control [129], [130]. Typically, sensors such as encoders or resolvers are mounted on the shaft of the rotor to obtain exact rotor position information. Even though encoders have exceptional performance as far as resolution is concerned, resolvers on the other hand can cope very well in severe and harsh conditions for extremely long periods, hence they usually rank as the perfect choice in most PMSM applications.

Interfacing between the resolver and the system microprocessor, a Resolver-to-Digital (RDC) uses sine and cosine signals to decode the angular position and rotational speed of the motor shaft. The level of precision with which RDCs work is of utmost importance mainly because when vector control is carried out with rotor position information which is tainted with position errors, it leads to the generation of periodic torque ripples. Consequently, considerable level of research has been carried out to improve the measurement accuracy of RDCs. Resolvers are not built to generate immaculate output signals. Actual resolver output signals possess nonideal characteristics like harmonic distortion, quadrature error, shift of reference phase angle and amplitude imbalance [131], [132], therefore there is usually a high probability for rotor position distortion. The amplitude imbalance of output signals which happens to be the most pervasive nonideal property is typically caused by disparity in transformer turns ratio, mismatches in excitation signal and the nonlinear properties exhibited by the signal processing devices [133]. Considerable level of research has been conducted over the decades on how to effectively resolve resolver-errors. For instance after an exhaustive analysis, a compensation algorithm is developed in paper [131], which significantly minimizes the most prevalent errors which occur in typical resolver-inspired position sensing systems. This scheme nevertheless requires substantial time, effort and significant level of signal processing. In literature [132], a strategy aimed at diminishing the torque ripples caused by amplitude variation is introduced. The method needs an extra position sensor that does not contain any distorted position information to enable it minimize torque ripples. The approach is incomplete because in order to permit precise PMSM vector control using a resolver, amplitude imbalance cannot be independently considered. It must be considered simultaneously with quadrature imperfection for accurate vector control to occur [134]. The authors in [135] put forward a compensation method to correct the phase and scale errors for a typical PMSM compatible with a resolver. In the

approach, the compensator is made to receive the d-axis current as an input signal to calculate position errors by utilizing integral operations according to the rotor position. However, this method can only be modified in motor drive systems mainly because position errors can be extracted from the d-axis current. A DC offset and scale compensation method is proposed in [136] when the motor is not operating. It can be modified in a digital signal processing (DSP) system based on RDC and utilized, however it remains incomplete in [136] because a mathematical procedure was not used. Reference [134] proposes a classification and compensation technique for a DSP system based on RDC, in which case the output signals of the resolver can directly be utilized. The radius and the area of the circle swept by the resolver signals provide crucial information for classification and compensation of errors. The strategy in essence calculates the integration of the areas traversed by the resolver signals to classify and compensate for only the offset and scale errors. Though experimental results verified the effectiveness of the proposed method, the design only worked for steady state conditions but generated significant errors in the transient state. It also could not compensate for phase errors. A novel compensation algorithm is proposed to minimize position errors introduced by the amplitude mismatch of the resolver output signals in [133]. An integral operation of the resolver to digital position to the specified rotor position, detects the amplitude of the position error. The proposed algorithm compensates for the distorted rotor position with few computational steps and does not require additional hardware [133].

2.3.4 ADC/Microcontroller-related Errors

Fig. 2-12 depicts the pathway traversed by a sensor signal to the microcontroller. The signal conditioning/regulation circuits play a vital role in reducing the analog signal from the resolver (15V) to reasonable limits (approximately 3.3V) prior to interfacing it with the ADC within the microcontroller. Errors could be generated from any of the components shown in Fig. 2-12. The ADC has a high susceptibility to errors. As its name suggests, it is a device which converts analog signals in a defined range to digital outputs. The precision of the analog-to-digital conversion has an impact on the overall system quality and efficiency. To improve the accuracy, it is important to understand the errors associated with the ADC and the parameters affecting them. The ADC cannot single-handedly ensure the precision of results, it relies on the overall system design. Irrespective of how it accomplishes the task, an ADC produces a digital output with a finite number of bits from an analog input signal, a process known as quantization. The

quantization error is the unavoidable result of this process. The quantization process leads to a staircase transfer function.

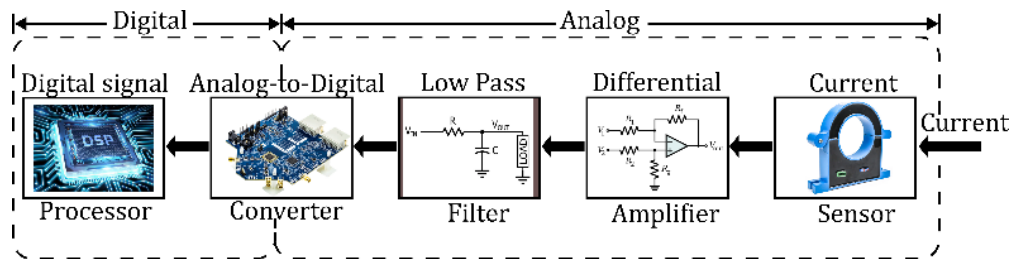


Fig. 2-12. Sensor data acquisition and system components.

Different techniques exist for converting analog signals to their respective digital outputs. Available ADC architecture for microcontroller/DSP applications within motor drives include Successive Approximation Register (SAR), Sigma Delta (SD or $\Sigma\Delta$), Slope or Dual slope, Pipelined and Flash ADC. The SAR ADC is the most popular due to exceptional power efficiency [137]. The SAR ADC shown in Fig. 2-13 is initiated by forcing the most significant bit (MSB) high (for instance in a typical 8-bit ADC it becomes 1000 0000), then the Digital-to-Analog Converter (DAC) converts it to $V_{\text{AREF}}/2$, where V_{AREF} is the reference voltage. The comparator then compares the input voltage with $V_{\text{AREF}}/2$. If the input voltage is greater than the voltage corresponding to the MSB, the bit is set, otherwise it is reset. After this comparison is done, the next significant bit is set to $V_{\text{AREF}}/4$ and a comparison is again performed with the input voltage. The stages are repeated till all the bit positions have been compared. At the end of all the bit comparisons, a corresponding digital output for the analog input is obtained [138]. The more bits there are in the output, the closer the digital outcome will be to the analog signal.

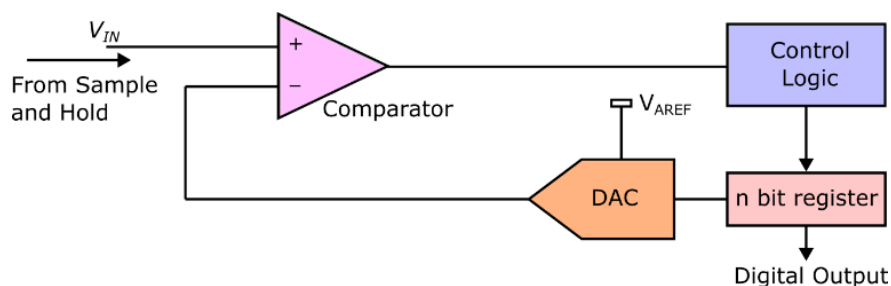


Fig. 2-13. SAR ADC block diagram.

According to the block diagram description of Fig. 2-14, the ADC can be divided into the following segments:

- Analog input pins
- Analog multiplexer
- Sample and Hold circuit
- Successive approximation block
- Control block
- Analog supply/reference

The accuracy of the ADC impacts the overall system quality and efficiency. To improve precision, a thorough understanding of the errors associated with the ADC and the parameters affecting them is required. Nevertheless, the elimination of fundamental errors associated with ADC architectures constitutes a major challenge. ADC errors can be classified as those related to itself and those related to the external environment. Self-related ADC errors include Offset error, gain error, Full Scale error, Differential Nonlinearity and Integral Nonlinearity (INL).

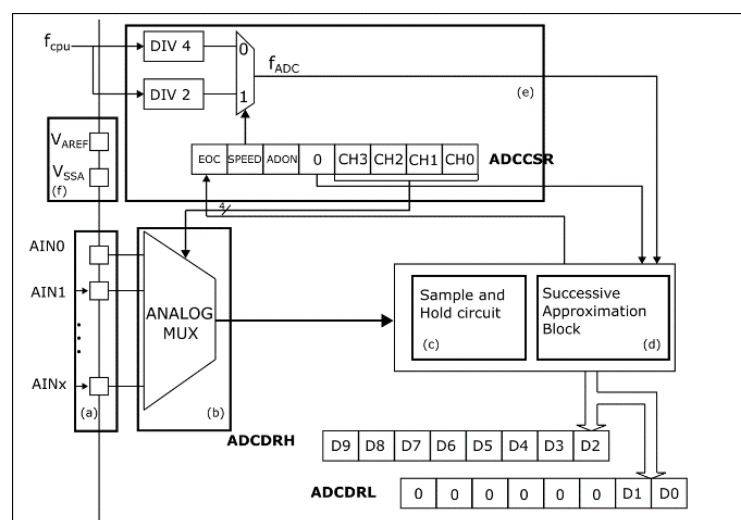


Fig. 2-14. Block diagram of ADC [138].

Offset Error: It is defined as the deviation of the actual ADC's transfer function from the perfect ADC's transfer function at the point of zero to the transition measured in the least significant bit (LSB). An offset error occurs when the transition from output value 0 to 1 does not occur at an input value of 0.5LSB . If the actual transfer function lies above the ideal line,

there is a positive offset and vice versa. Fig. 2-15 (a) and (b) depict the positive and negative offsets illustrated with double-ended arrows. Generally, the offset errors limit the available range for the ADC. A large positive offset error causes the output value to saturate at maximum before the input voltage reaches its maximum. A large negative offset error gives an output value of zero for the smallest input voltages [139].

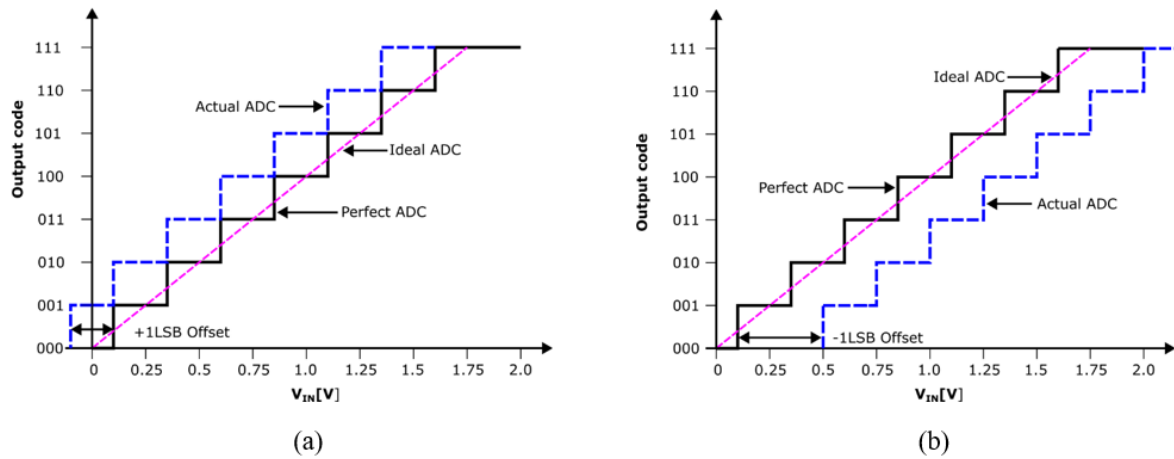


Fig. 2-15. ADC offset error for (a) positive instance. (b) negative instance.

Gain Error: This is defined as the deviation of the last step's midpoint of the actual ADC from the last step's midpoint of the ideal ADC. These errors cause the actual transfer function slope to deviate from the ideal slope. If the transfer function of the actual ADC occurs below the ideal straight line, then it produces a negative gain error and vice versa. The gain error is estimated as the number of least significant bits (LSBs) from a vertical straight line drawn between the midpoint of the last step of the actual transfer curve and the ideal straight line. In the positive gain error scenario depicted in Fig. 2-16 (a), the output value saturates before the input voltage reaches its maximum. The vertical arrow shows the midpoint of the last output step. In the negative gain error instance shown in Fig. 2-16 (b), the output value has only reached six when the input voltage is at its maximum. This leads to a negative deviation for the actual transfer function.

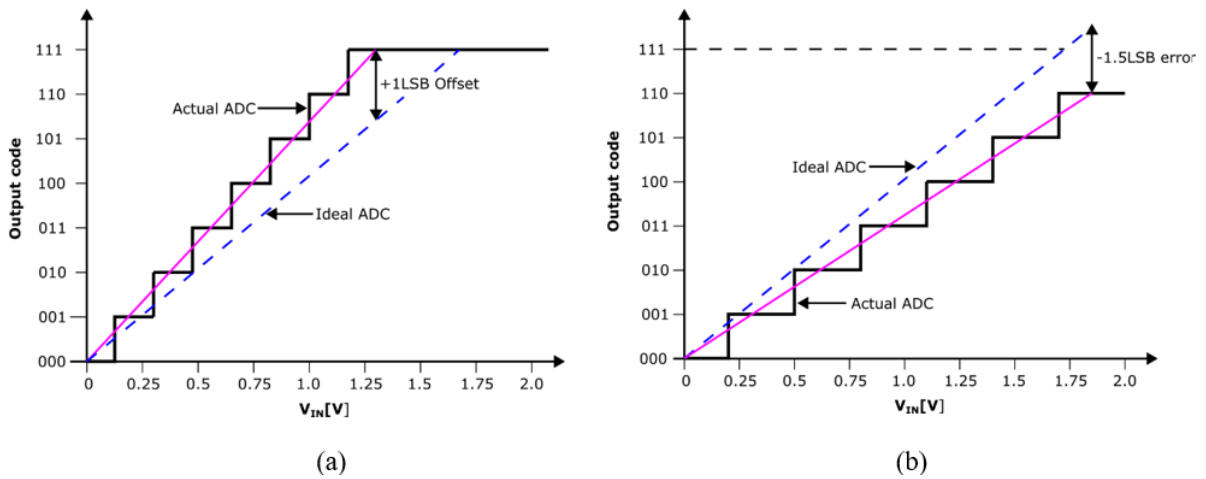


Fig. 2-16. ADC gain error for (a) positive case. (b) negative case.

Full Scale Error: Is the deviation of the last transition of the actual ADC from the last transition of the perfect ADC, measured in LSB. The Full Scale error depicted in Fig. 2-17 emanates because of both gain and offset errors. The deviation between the actual ADC and the ideal ADC is 1.5 LSB.

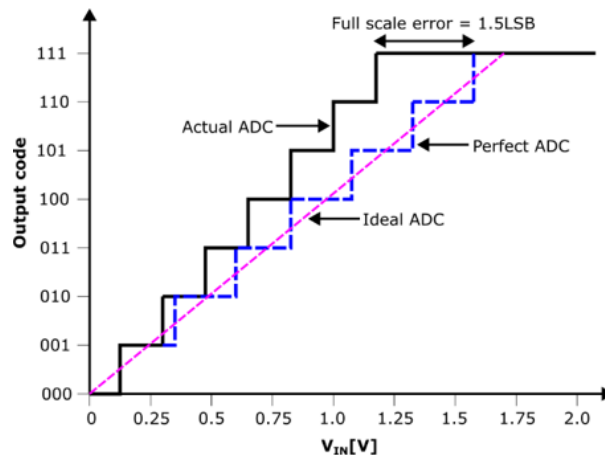


Fig. 2-17. ADC full scale error.

Differential Nonlinearity (DNL): It is defined as the maximum and minimum difference in the step width between the actual transfer function and the ideal transfer function. As shown in Fig. 2-18, DNL produces quantization steps with varying widths, some narrower (negative DNL) and some wider (positive DNL). An ideal device has a DNL of zero (all steps are of equal size). All ADCs can exhibit both positive and negative DNL at distinct locations on the

transfer curve. The nonlinearity introduced by DNL errors can cause signal distortion, resulting in the spread of the signal energy across multiple frequency components.

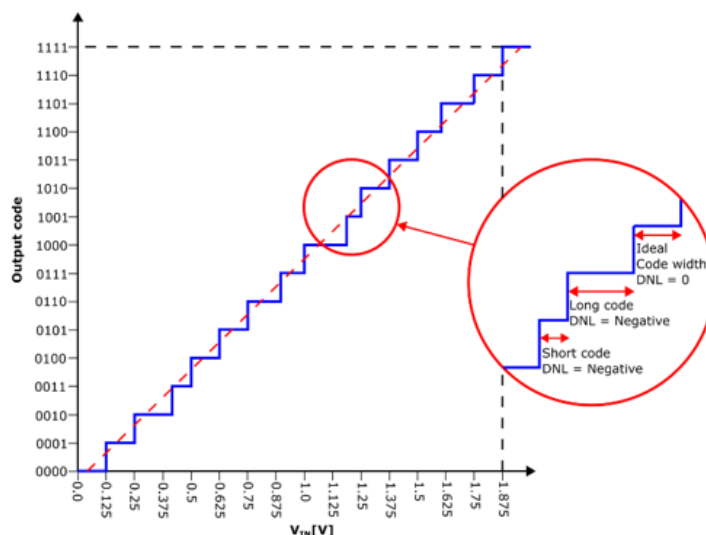


Fig. 2-18. ADC DNL [140].

ADC Missing Code: There are certain unique instances where the actual transfer function would look as depicted in the Fig. 2-19. The first code change (from 000 to 001) in the figure is caused by an input change of 0.25V. The second move, from 001 to 010 has an input change that is 1.25LSB which is increased by 0.25LSB. The input for the third transition remains intact at the correct size. The digital output remains unchanged when the input voltage transitions from 1V to 1.5V and output code 100 remains missing. Generally, the higher the resolution of the ADC, the lesser the chances of having to deal with the missing code phenomenon. An ADC with DNL error less than ± 1 LSB guarantees no missing code [141].

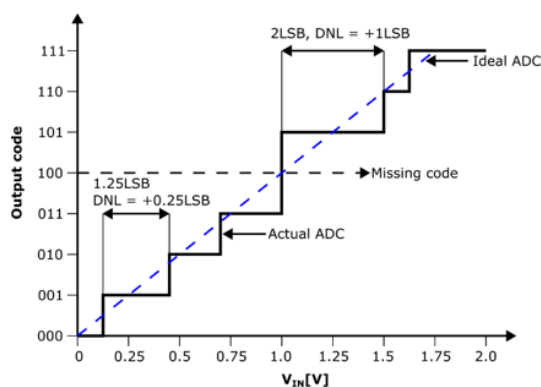


Fig. 2-19. ADC Missing code.

Integral Non-Linearity (INL): This is the maximum vertical difference between the actual and the ideal curve. It is a measure of how much the actual curve deviates from the ideal transfer curve. It can be interpreted as the integral of DNLs over a full range. For a positive INL, the actual curve is above the ideal ADC and vice versa. To measure the INL the midpoints of all the output steps of the actual ADC are connected and the maximum deviation from the ideal curve in terms of LSBs is then found. The maximum INL depicted in Fig. 2-20 is +0.75LSB.

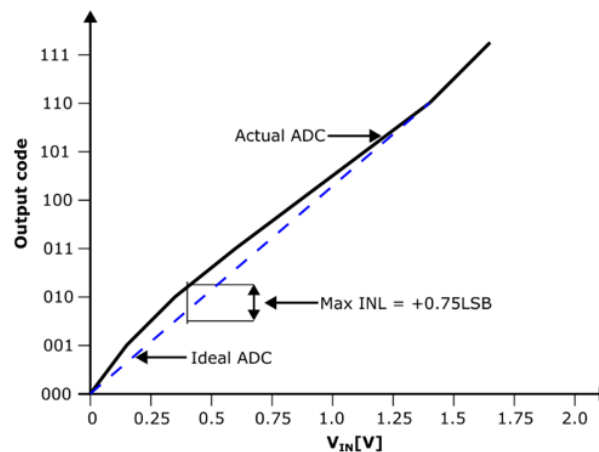


Fig. 2-20. ADC INL.

Total Unadjusted Error (TUE): This is defined as the maximum deviation between the actual and the ideal transfer curves. It is a parameter which specifies the total amount of error likely to occur, causing maximum deviation between the ideal digital output and the actual digital output. The TUE according to Fig. 2-21 is the maximum deviation which exists between the ideal expected value and the actual value obtained from the ADC for random input voltages. It is not the sum of offset error, gain error, differential linearity error and the integral linearity error. While the offset error affects the digital results at lower voltages, the gain error does the opposite, it affects the digital output for higher voltages.

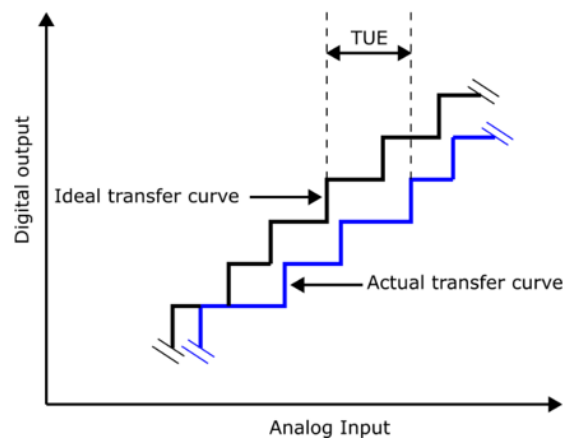


Fig. 2-21. Total Unadjusted Error [142].

On the other hand, typical examples of ADC errors related the whole system include the reference-voltage noise, analog-input signal noise, ADC dynamic range, temperature impact and the analog signal source resistance.

Reference-Voltage Noise (Power Supply Noise): As the ADC output is the ratio between the analog-signal voltage and supply/reference voltage, any noise appearing on the analog reference will cause a variation in the converted digital value. For instance, with an analog reference of 3.3V ($V_{AREF} = V_{DDA}$) and a 1V signal input, the converted result is $(1/3.3) \times 4095 = 4D9h$. With a 40mV peak-to-peak ripple in the analog reference, the converted value becomes $(1/3.34) \times 4095 = 4CAh$ (with V_{AREF} at its peak location). Hence the error can be calculated as $\text{Error} = 4D9 - 4CA = 15\text{LSB}$. Typically, the switch-mode power supply (SMPS) has fast in-built switching power transistors. This leads to the introduction of high-frequency noise in the output, usually in the range of 15KHz to 1MHz [142], [143].

The Analog Input Signal Noise: It is possible that the analog signal to be converted may have some noise superimposed on it. This could be a high frequency noise signal. From Fig. 2-22, by comparing the ideal analog input signal to its actual value, it is evident that the actual analog input signal has some induced 5mV Vp-p noise, which losses 2LSB for a 10-bit resolution ADC.

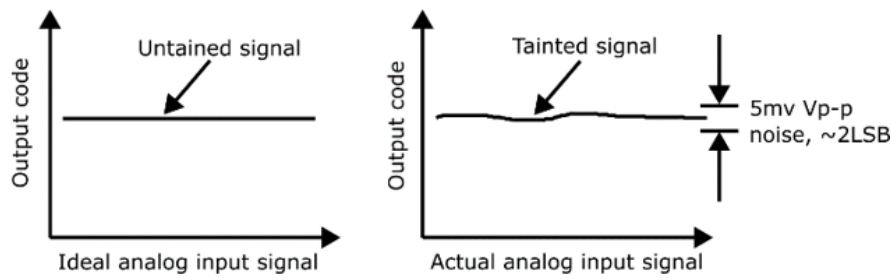


Fig. 2-22. Noise within the Analog input signal.

ADC Dynamic Range: To ensure that the maximum ADC conversion accuracy is obtained, the ADC dynamic range must match the maximum amplitude of the signal. For example, assuming the signal to be converted ranges between 0 to 2.5V with VAREF set to 3.3V then the maximum signal value converted by the ADC in Fig. 2-23 is 3102 (2.5V). This implies there are 993 unutilized transitions ($4095 - 3102 = 993$), which signifies a loss in the converted signal precision especially if the ADC linearity performance is non-ideal.

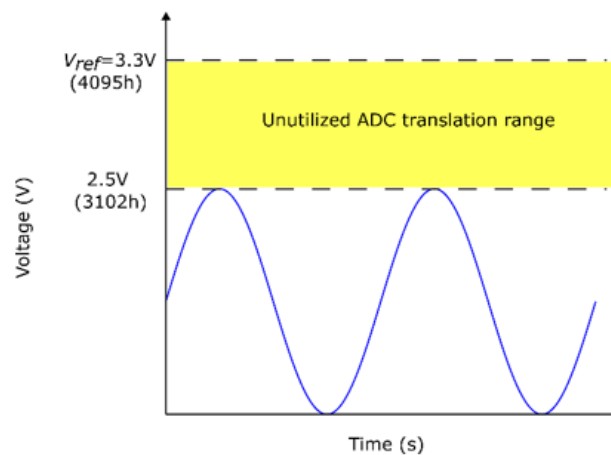


Fig. 2-23. ADC dynamic range [142].

Temperature Impact: The temperature influence on ADC precision typically reflects as offset error drift and gain error drift. These errors can be compensated in the microcontroller firmware in certain instances with reasonable effort. The ADC reference voltage varies with temperature variation, irrespective of the microcontroller unit's internal or external voltage reference utilized.

Analog Signal Source Resistance: The series resistance (R_{IN}) or the analog signal source impedance between the source and the pin causes a voltage drop across it due to the current

flowing into the pin. The charging of the internal sampling capacitor ($C_{s/h}$) is regulated by the switch with resistance $R_{s/h}$. With the inclusion of the source resistance (R_{IN}), the time required to fully charge the hold capacitor increases. Fig. 2-24 portrays the impact the analog signal source resistance has on the conversion. The effective charging of $C_{ADC} = C_{IN} + C_{s/h}$ is controlled by $R_{IN} + R_{s/h}$, hence the charging time constant becomes $t_c = (R_{IN} + R_{s/h}) \times C_{ADC}$. The settling time needed to safely sample the input is given by $t_c \times$ multiplier, where the multiplier is 6.93, 8.3 and 11, respectively for ADC resolution of 10, 12 and 16 bits [142]. If the sampling time is less than the settling time required (time required to charge the C_{ADC} through $R_{IN} + R_{s/h}$ fully), the digital value converted by the ADC will be less than the actual value.

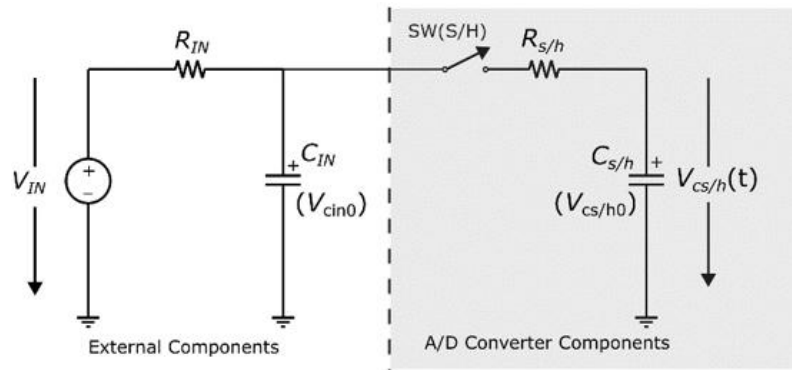


Fig. 2-24. Analog signal source resistance [138].

ADC accuracy is fixed by its principle, design, and implementation but can also be improved by several hardware and/or software strategies. Hardware approaches improve ADC results by altering the environment around the ADC to obtain more accurate ADC output. Software schemes try to improve the raw ADC results via postprocessing methods. A significant level of CPU power is needed to perform these methods which can be implemented in the microcontroller firmware [141]. As far as the reduction of the effects of ADC-related errors goes, it is noteworthy to point out that it is complex to calculate the INL and DNL as they depend on the ADC design. They can be calibrated by the measured ADC curve stored in the microcontroller memory; however, this requires calibration of each device in the final application. Since the INL is the integral of the DNL, it can be considered an indicator of maximum error that may occur at any digital step. The offset and gain errors on the other hand can be compensated by the microcontroller firmware [142].

Approaches to reduce the ADC errors related to the external environment include thoroughly checking the reference voltage and power supply, eliminating the analog-input signal noise, matching the ADC dynamic range to the maximum signal amplitude and establishing uniformity in the analog-source resistance. Additional measures include frequently examining temperature effect compensation and utilizing software strategies to improve accuracy. Concerning software strategies aimed at accuracy improvement, the precision of sampling depends on both software and hardware modules. It is impossible to get an ideal precision with only one of them. Some simple, yet effective procedures to enhance accuracy include the following:

Averaging Samples: Though the averaging of samples reduces speed, it can provide improved precision. SAR-ADC supplies register settings to perform hardware averaging. The hardware and software averaging are similar. However, the software averaging offers better accuracy than hardware averaging, even though it is slower [141].

Increase of Over-Sampling-Rate (OSR): Increasing OSR can improve the precision. This can be achieved through adjustment in the register settings.

Calibration of ADC: The offset, the gain and the bit weight calibration decrease the internal ADC errors. However, the internal ADC structure must be known.

Reducing Internal Noise Generated by CPU: This is achieved by designing firmware to utilize minimum disturbance from the microcontroller during ADC conversion. The use of ADC internal asynchronous clock will significantly minimize the digital noise coupled to the ADC [142].

Table 2-4 depicts examples of common errors which could emerge from primary powertrain components during regular operation. Effective solutions for the errors as well as merits and demerits of the proposed schemes aimed at resolving the errors have all been provided.

TABLE 2-4 Summary of the Sources of Error from Key Powertrain Components

Source of Error	Type of Error	Solution for Error	Merit	Demerit	Ref
PMSM	Static Eccentricity	Use of an incremental inductance approach for the detection of static eccentricity under	Scheme utilizes DC values of the q-axis voltage hence the use of controller bandwidth	Controller designed for the off-line testing is aimed at controlling both speed and saturation	[144]

		off-line condition.	becomes unnecessary.	simultaneously, hence it is difficult to tell which parameter detects static eccentricity.	
Inverter	Dead-time current harmonics	Suppression of current distortion utilizing Least-mean Square (LMS) algorithm.	Algorithm can directly generate compensation voltage references without voltage error estimation.	In the transient states, the frequency of the reference inputs of the algorithm needs to be constantly adjusted according to the motor speed.	[145]
Current Sensor	DC Drift error	Modification of Clarke coordinate transformation to decouple dc-drift error in $\alpha - \beta$ axis current components.	Reconstructed phase currents contain low level of distortions and harmonic contents.	Use of notch filter for compensation of the dc drift error can introduce unwanted distortion outside of the notch frequency.	[146]
Position Sensor	Low resolution position sensor error	Improvement of position and speed estimation through polynomial fitting scheme and state observer techniques.	The use of binary Hall position sensors guarantees both excellent control performance and low cost.	The Hall position sensors are vulnerable to load disturbance.	[147]
ADC	Settling error	Utilization of Digital Error Correction (DEC) approach to alleviate error and improve ADC conversion rate.	The strategy incurs no offset to the ADC, while maintaining the straightforward timing logic.	Algorithm requires four redundant capacitors and conversion cycle.	[148]

2.4 Errors Under Fault Tolerance Operation

2.4.1 Position Sensorless Approach

In space-limited applications, the installation of a sensor on the rotor tends to be problematic, hence over the last few decades, alternative approaches to estimating precise rotor position

have been proposed [102], [149]. There are two main approaches as far as the sensorless estimation of position and speed is concerned. Fig. 2-25 shows a simplified picture of the main sensorless control approaches and their subdivisions.

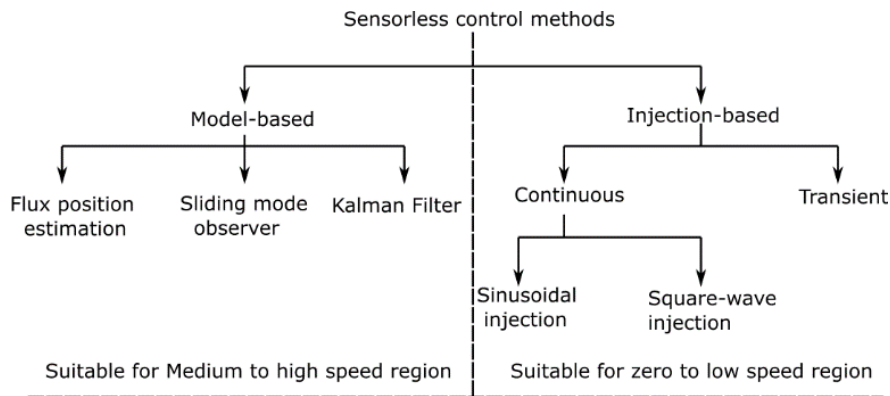


Fig. 2-25. Categorization of Position sensorless control.

a) Error Analysis in the Back Electromotive Force (EMF) Approach: This strategy also known as the Model-based scheme, provides great performance at medium to high speeds, but malfunctions at zero (or near zero speeds). Since the magnitude of the back EMF is proportional to the rotor speed, at low speeds the EMF almost diminishes to zero [150]. This approach involves the use of several observers (disturbance, state and sliding mode) [151], [152], [153], [154] and Kalman filters [155]. The values obtained from the back EMF method are contaminated by a significant level of estimation errors caused by inverter nonlinearity [156], temperature changes, impact of magnetic and mechanical tolerance. These errors adversely affect the rotor position and speed estimates, which ultimately deteriorates the precision of the control mechanism, hence it requires considerable attention. To resolve these estimation errors, researchers in [157], [158] suggested putting more emphasis on motor design and wisely choosing permanent magnet materials which have a great response to wide temperature variation to help alleviate such estimation errors. The harmonic components within these estimation errors tend to have an immunity to the suggested techniques though. It is difficult to sieve them especially in surface-mounted PMSM (SPMSM) based drives mainly due to two reasons [159].

According to [159], for non-salient machines (SPMSMs), irrespective of how close two pieces of magnets are placed, a gap always exists between them resulting in high-order harmonic content appearing in the back EMF estimates. The second reason is the non-linear nature of

inverters, which leads to sixth-order harmonic components showing up in the back EMF estimates. Myriad rotor position error detecting strategies meant to eliminate the harmonic component in the back EMF estimates have been proposed [160], [161], [162], [163]. The authors in [164] used an Adaptive Notch Filter(ANF) Phase-Locked Loop (PLL) ANF-PLL processing scheme to sieve out the fifth and seventh-order harmonics in the estimated back EMF of a sliding mode observer-inspired sensorless interior PMSM (IPMSM). The efficacy of the scheme was carried out analytically on a 2Kw IPMSM sensorless drive, with satisfactory experimental results.

The harmonic content within the EMF of salient motors differs from non-salient motors. They tend to be more serious in non-salient motors due to the existence of gaps between the permanent magnet of the rotor configuration [159]. The ANN-PLL processing strategy, which generally filters out harmonics convincingly becomes incompetent for non-salient motors since the largest harmonic component in the EMF of such motors is of the third order. Since the harmonic errors of the estimated EMF signal are hard to be eliminated within SPMSMs, an improvised version of the ANF called the Synchronous Frequency-extract Filter (SFF) is proposed in literature [159] to extract the fundamental wave of the rotor position estimation prior to applying it to the PLL. The combination of the SFF and PLL was found to compensate for the estimated back EMF harmonic error effectively.

To expound on the nature of the contamination, the position estimation error generally consists of a DC drift and a harmonic ripple [165]. The influence of inverter nonlinearities and flux spatial harmonics allow $(6k \pm 1)$ th harmonics to appear in the EMF estimates, leading to $(6k)$ th harmonic ripples within the estimated rotor position and speed. For the sake of analysis of position estimation error due to the harmonics within the estimated back-EMF, the classical voltage equation for an IPMSM in the α - β stationary reference frame is modified to obtain this new voltage model [165].

$$\begin{bmatrix} V_\alpha \\ V_\beta \end{bmatrix} = \begin{pmatrix} R + pL_d & \omega_e L_d - L_q \\ -\omega_e(L_d - L_q) & R + pL_d \end{pmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} + e_f + e_h \quad (2-4)$$

where R is the stator resistance, L_d and L_q are the stator inductances, ω_e is the electrical rotor speed, p represents the differential operator, $V_{\alpha,\beta}$ and $i_{\alpha,\beta}$ denote the stator voltages and currents respectively in the $\alpha\beta$ -axis, while e_h and e_f represent the $(6k \pm 1)$ harmonics and the fundamental component contained within the back-EMF estimate. They can be represented as:

$$e_f = \begin{bmatrix} e_{f\alpha} \\ e_{f\beta} \end{bmatrix} = \begin{bmatrix} -e_1 \sin(\omega_e t + \theta_{e1}) \\ e_1 \cos(\omega_e t + \theta_{e1}) \end{bmatrix} \quad (2-5)$$

where $e_{f\alpha,\beta}$ is the component of the extended EMF associated with the fundamental.

$$e_h = \begin{bmatrix} e_{h\alpha} \\ e_{h\beta} \end{bmatrix} = \begin{bmatrix} -e_{6k-1} \sin(-(6k-1)\omega_e t + \theta_{e(6k-1)}) \\ e_{6k-1} \cos(-(6k-1)\omega_e t + \theta_{e(6k-1)}) \end{bmatrix} + \begin{bmatrix} -e_{6k+1} \sin((6k+1)\omega_e t + \theta_{e(6k+1)}) \\ e_{6k+1} \cos((6k+1)\omega_e t + \theta_{e(6k+1)}) \end{bmatrix} \quad (2-6)$$

where $e_{h\alpha,\beta}$ denotes the component of the extended EMF associated with the harmonics, whiles e_{6k-1} and e_{6k+1} represent the amplitudes of the $(6k-1)$ th and the $(6k+1)$ th harmonic constituents and $\theta_{e(6k-1)}$ and $\theta_{e(6k+1)}$ represent the corresponding initial phases respectively. By the help of the heterodyning procedure the phase difference can be obtained and represented as follows:

$$\begin{aligned} \varepsilon_\theta &= -e_\alpha \cos \hat{\theta}_e - e_\beta \sin \hat{\theta}_e \\ &= -(e_{f\alpha} + e_{h\alpha}) \cos \hat{\theta}_e - (e_{f\beta} + e_{h\beta}) \sin \hat{\theta}_e \\ &= e_1 \sin[(\omega_e - \hat{\omega}_e)t + \theta_{e1} - \hat{\theta}_{ei}] \\ &+ \sum_{k=1}^n e_{6k-1} \sin[-(6k-1)\omega_e - \hat{\omega}_e)t + \theta_{e(6k-1)} - \hat{\theta}_{ei}] \\ &+ \sum_{k=1}^n e_{6k+1} \sin[(6k+1)\omega_e - \hat{\omega}_e)t + \theta_{e(6k+1)} - \hat{\theta}_{ei}] \end{aligned} \quad (2-7)$$

where $\hat{\theta}_e$ represents the estimated rotor position, $\hat{\theta}_{ei}$ refers to the initial phase angle of the rotor position observation, whiles $e_{\alpha,\beta}$ is the value of the extended EMF in the α -axis and β -axis respectively and $\hat{\omega}_e$ is the estimated electrical rotor speed.

From equation (2-7), the phase difference results in two high frequency (HF) components with the other term excluding HF constituents. Through the convergence of the position estimator, (2-7) can be simplified as:

$$e_\theta = e_1 \sin(\theta_{e1} - \hat{\theta}_{ei}) + \sum_{k=1}^n e_{6k} \sin(6k\omega_e t + \theta_{e(6k)}) \quad (2-8)$$

where e_{6k} represents the amplitude of the equivalent $6k^{\text{th}}$ back-EMF harmonics and $\theta_{e(6k)}$ represents the initial phase. The $6k^{\text{th}}$ back-EMF harmonics will manifest as supplementary

errors which exist in the phase difference. Hence the rotor position will contain the $6k^{\text{th}}$ harmonics, which will have to be eliminated to enhance rotor position estimation precision.

Besides the rotor position error-detecting algorithms which have already been mentioned earlier on, others such as the Adaptive Linear Neural (ADALINE) network-based filters have proven to be effective harmonic detection strategies that help to suppress the harmonic ripples. The scheme provides excellent precision and convergence speed in pursuing and compensating harmonic contents due to its simple make-up and characteristic of the supervised learning mechanism [166]. The ADALINE network has the flexibility of making a system operate optimally by constantly self-tuning the filter weights based on filter signal properties and operating environment. Typical approaches used to update the ADALINE filter weights include Least Mean Square (LMS) and Recursive Least Square (RLS) algorithms.

The Second-Order Generalized Integrator (SOGI) which exhibits great performance in signal processing for distorted and asymmetric systems has found great application in power grid and renewable energy sectors due to its affinity to detect selected frequency harmonics [167]. Researchers put forward a synchronization strategy based on an adaptive filter implemented using a SOGI, which was self-tuned to grid frequency, attributable to the action of a Frequency-Locked Loop (FLL). The system can carry out an outstanding estimation of the instantaneous symmetrical components of the grid voltage under uneven and distorted grid conditions. The approaches utilizing SOGI to detect the harmonic constituents and extract the fundamental frequency components in the grid have the advantage of frequency adaptive performance, low computational burden and relatively high filtering capability. Considering these attributes, the SOGI scheme can be adopted in sensorless IPMSM drives to extract the harmonic components in the EMF estimates to eliminate the harmonic error in the position estimation [165].

In [168], to minimize the position estimation error with harmonic fluctuations for position sensorless IPMSM drives, a multiple Adaptive Vector Filter (AVF) Cross-Feedback Network (CFN) is proposed for a model-based position observer. To obtain the back-EMF information, a full-order Luenberger observer is used. The harmonic fluctuations within the position estimation error because of inverter nonlinearities and flux spatial harmonics are examined. Correspondingly, a newly proposed multiple AVF-CFN with a simple structure is adopted to spot and compensate the back-EMF distortions and consequently get rid of the position error harmonic variation. Hence the position estimation accuracy can be enhanced, which improves the position sensorless control performance in the long run [165].

b) Error Analysis in the High Frequency Signal Injection Approach: This other sensorless rotor position estimation method shows phenomenal performance at zero and low speeds. It takes advantage of the inherent saliency of IPMSMs to inject high frequency stator voltage signals to interact with machine saliency in order to extract rotor position. It is ineffective in SPMSMs due to the nonexistence of saliency. This high frequency signal injection approach can be classified into continuous and transient injection methods [169], [170], [171]. In the continuous method, a sine, square wave or a pulsating signal with uninterruptedly high frequency is made to overlap with the fundamental excitation (having a high amplitude), whereas in the other approach, the rotor position information is extracted from the transient response of the stator current after the application of an impulse voltage vector [172], [173]. The production of torque ripples, harmonic losses and acoustic noise is a major flaw to these signal injection methods. Papers [174], [175] introduced a compensation technique focusing on utilizing high frequency signal injection to suppress the acoustic noise to proportionally low levels, albeit the torque ripples and harmonic losses remained intact. In some literatures, position estimation strategies which utilize current derivatives have been proposed to avoid the major flaws of the signal injection methods. However, in these estimation schemes, the precision of the sampled current derivatives is crucial in calculating the rotor position.

In a typical FOC algorithm platformed on standard vector control principles, the Zero-Voltage Vector (ZVV) period can be utilized to calculate the current derivatives since a control period comprises effective vectors and ZVVs [102]. In [176], [177], [178], [179], [180] position estimation schemes which utilize accurately sampled current derivatives are proposed to bypass the flaws introduced by the high frequency injection methods. In the low-speed region, the zero-voltage time shoots up massively as a result of the low-amplitude back EMF. This low-speed tendency paves way to obtain three phase currents and their derivatives during the zero voltage time [102]. References [36] and [38] take advantage of this principle to put forward low-speed estimation strategies aimed at calculating current derivatives during ZVV period, where the switching rules between disparate load regions are manipulated to obtain the desired full-load range operation. In [179] a q-axis current-inspired position estimation strategy which does not utilize switching manipulation is introduced. However, a d-axis current injection with a high amplitude is needed from zero load to rated load. Paper [102] proposes a position estimation method which focusses on how to efficiently extract rotor position information from ZVV period and further elucidates how to improve the precision of the estimated position, all the while avoiding the use of high frequency injection. The proposed scheme is straightforward

to implement, requiring mere current shunt resistors, with the d-axis current injection not necessary unlike the proposal in [179].

2.4.2 Three-phase Four-switch Devices Fault-tolerant Operation

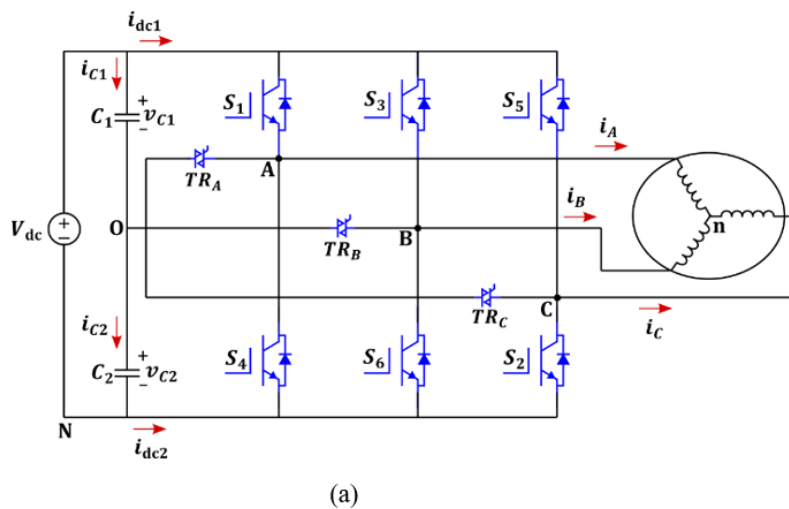
Due to the high failure rate of power inverters, corresponding fault-tolerant inverter topologies and control strategies are required to enable safe post fault operation within motor drive applications. The Three-Phase Four Switch (TPFS) inverter or Four-Switch Three-Phase (FSTP) inverter, as known in other literature has been utilized as a very favourable fault-tolerant topology for the traditional Three-Phase Six-Switch (TPSS) inverter to ride through open/short circuit faults. In simple terms, the TPFS inverter can be described as a post-fault reconfigured topology for a two-level inverter after one of its legs has witnessed a failure or breakdown. Evidently, the reconfiguration reduces the number of switches available for normal operation from six to four. This reduction translates to lower conduction and switching losses, reduced number of interface circuits to supply logic signals for the switches, simple control algorithm to generate logic signals and less real-time computational burden [181]. As a result of the reconfiguration, the control system is modified to adapt circuit changes since the inverter topology changes from TPSS to TPFS to obtain optimal performance of the drive.

The fault-tolerant topology of the power inverter is depicted in Fig. 2-26 (a). It is constructed by inserting triacs/bidirectional triode thyristors (TR_A, TR_B, TR_C) in the circuit. Six IGBTs are employed as power switches (for DC to AC operation) and the DC-link capacitors are assumed to have the same value ($C_1 = C_2 = C$). The voltages on these two capacitors are v_{c1} and v_{c2} respectively. N denotes the negative DC-link point whereas n represents the neutral point of the three-phase load. Normally, the fault-tolerant control process comprises four stages: diagnosis of the fault, separation of faulty part from healthy segments, inverter topology reconfiguration and the control for the post-fault operation [182]. In the event of a switch breakdown or failure, the corresponding triac is activated to isolate the faulty leg and connect the corresponding phase to the midpoint of the DC-bus. For instance, if switch S_1 or S_4 breaks down to form an open circuit, the TPFS topology for the inverter is constructed in Fig. 2-26 (b).

Even though in the TPFS topology the connection of one of the motor terminals to the center of the DC-link capacitor minimizes the number of power switches and leads to cost reduction, there are disadvantages with this configuration. The voltage utilization factor is halved

compared to the TPSS inverter setup. Specifically, the peak phase voltage of the TPFS inverter is $V_{dc}/2\sqrt{3}$, while that of the TPSS inverter is $V_{dc}/\sqrt{3}$. Additionally, the capacitor center tap voltage fluctuates and it destroys the balance which exists between the motor phase currents. The reason for this is that the current flow through a capacitor either increases or decreases the voltage steadily for each half cycle. Consequently, the voltage fluctuation increases as the load torque soars or the frequency diminishes [183]. Furthermore, the capacitor voltage fluctuations strongly affect the linear modulation range of the TPFS inverter. If the capacitor voltage fluctuations are ignored, the TPFS inverter fed PMSM drive may operate in the overmodulation zone with an imprecise DC-bus voltage, leading to the production of abundant low frequency torque harmonics. Moreover, operating in the overmodulation zone often requires higher switching frequencies and increased modulation index, resulting in higher switching losses in power switches. This can lead to inverter failure and torque pulsation. Since the DC-bus is divided into two parts by split capacitors, the modulation index of the DC bus voltage becomes invalid for performing sinusoidal PWM [184].

With the TPFS inverter topology, only four active vectors are available and the zero vectors are absent, which creates a challenge in the Space Vector PWM (SVPWM) for the TPFS inverter. The equivalent zero vectors are synthesized by the combination of the two opposite active vectors whose volt-second integral equates to zero. Since the absence of zero vectors tend to complicate the modulation strategies for the TPFS inverters, it has attracted notable research interest. The authors in [183], [185], [186] focused on compensated PWM schemes to eliminate unbalanced output currents caused by capacitor voltage discrepancy. In [184] and [187], two equivalent zero vector synthesis approaches are put forward, where the current distortion performances of both strategies are analysed and compared.



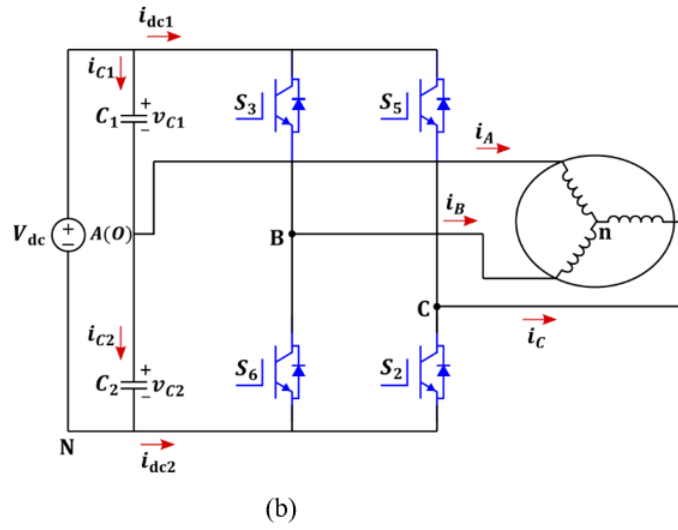


Fig. 2-26. VSI topology. (a) Fault-tolerant instance. (b) Post-fault TPFS [188].

The authors in [189] and [190] demonstrate that the current stress to the DC capacitors has direct relation to the utilized PWM strategies in fault-tolerant applications, and this information is crucial as far as the life cycle of the DC capacitors are concerned. The impacts of voltage vectors on the capacitor voltage offset are presented in [191], [192], [193], thus the DC-link voltage offset can be suppressed through the selection of precise voltage vectors during the control period. The effect of voltage variation on DC capacitors is also analysed. Just a handful of studies have been conducted on PWM strategies for TPFS inverters in terms of their impact on torque ripples in PMSM drives. Reference [194] alleviates torque ripples in TPFS inverter fed PMSM drives through the utilization of a hybrid Space Vector Modulation (HBSVM). In the scheme, to minimize the complexity of the proposed SVM strategy, a novel sector identification algorithm is additionally developed to eliminate the need for complex trigonometric function calculations.

2.4.3 Mathematical model of the TPFS Inverter-fed PMSM

In the TPFS Inverter-fed PMSM Drive topology depicted in Fig. 2-27, the split capacitors are assumed to be identical. For the sake of cost minimization, the phase A leg is omitted and instead, its stator is connected to the neutral point of the DC-split capacitors, to provide an available pathway for the stator current i_{sa} .

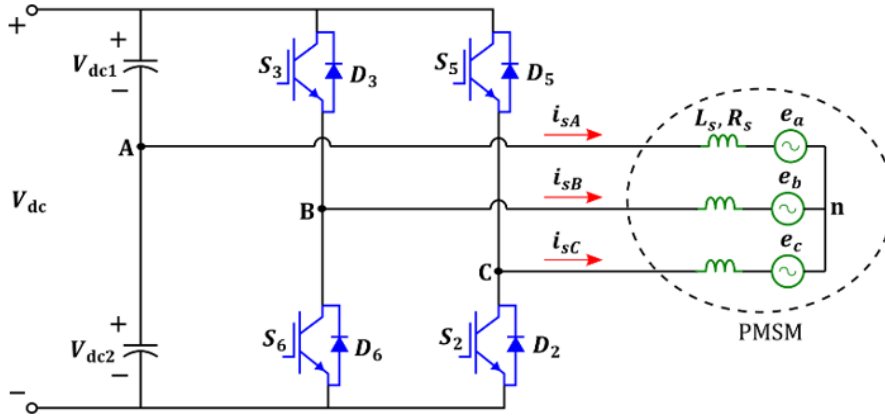


Fig. 2-27. TPFS inverter-fed PMSM drive configuration.

The stator resistance and inductance are denoted by R_s and L_s respectively. The classical PMSM stator voltage equation is expressed as follows:

$$v_s = R_s i_s + L_s \frac{di_s}{dt} + E = R_s i_s + \frac{d\lambda_s}{dt} \quad (2-9)$$

where $v_s = [v_{An}, v_{Bn}, v_{Cn}]^T$ is the stator voltage vector and $i_s = [i_{sA}, i_{sB}, i_{sC}]^T$ is the stator current vector, $E = [e_A, e_B, e_C]^T$ is the back electromotive force of the PMSM and λ_s is the stator linkage flux. The stator flux equation can then be represented in terms of the inductance and the rotor flux as

$$\lambda_s = L_s i_s + \lambda_f \quad (2-10)$$

where λ_f represents the rotor flux. The electromagnetic torque of the PMSM can be expressed as follows:

$$T_e = \frac{3}{2} p_n \lambda_s i_s \quad (2-11)$$

where p_n is the number of pole pairs. Within the synchronously rotating frame the torque can be expressed as follows:

$$T_e = \frac{3}{2} p_n [\lambda_f i_{sq} + (L_d - L_q) i_{sd} i_{sq}] \quad (2-12)$$

where the d-axis is aligned with the rotor flux. The Maximum Torque per Ampere (MTPA) is a widely utilized PMSM control strategy because the stator current can be fully exploited to

produce the maximum allowable torque. If the magnets happen to be mounted on the surface of the rotor, the d and q axis inductances are equal hence (2-12) can be simplified to

$$T_e = \frac{3}{2} p_n \lambda_f i_{sq} \quad (2-13)$$

Therefore, using the magnitude of λ_s , (2-13) can be further expressed as follows:

$$T_e = \frac{3}{2} p_n \lambda_f \frac{\lambda_{sq}}{L_q} = \frac{3}{2} p_n \lambda_f \frac{|\lambda_s|}{L_s} \sin \delta \quad (2-14)$$

where δ is the angle between λ_s and λ_f . Neglecting R_s , v_s and i_s lag λ_s and λ_f by 90° , respectively. δ is also the angle between v_s and i_s . In applying the MTPA algorithm, the magnitude of the stator flux and stator voltage at steady state can be expressed as follows:

$$|\lambda_s| = \sqrt{\lambda_f^2 + (L_s T_e / 1.5 p_n \lambda_f)^2} \quad (2-15)$$

$$|v_s| = \omega_r |\lambda_s| = \omega_r \sqrt{\lambda_f^2 + (L_s T_e / 1.5 p_n \lambda_f)^2} \quad (2-16)$$

Consequently, δ is expressed as follows:

$$\delta = \arccos \frac{\lambda_f}{|\lambda_s|} = \arccos \frac{\lambda_f}{\sqrt{\lambda_f^2 + (L_s T_e / 1.5 p_n \lambda_f)^2}} \quad (2-17)$$

Based on (2-9) - (2-17), the vectors of the PMSM under the influence of the MTPA strategy are shown in Fig. 2-28.

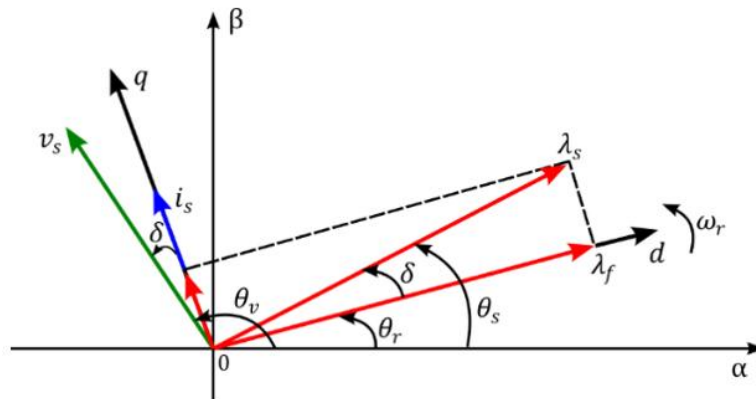


Fig. 2-28. Vector diagram of PMSM under MPTA influence [194].

In the depiction, the rotational speed of the rotor flux and the synchronously rotating d-q coordinates is denoted by ω_r and the position of the rotor flux is represented simply by $\theta_r = \omega_r t$. The positions of the stator flux and stator voltage are given by $\theta_s = \theta_r + \delta$ and $\theta_v = \theta_r + \delta + \pi/2$ respectively. It is worthwhile to note that in using the MTPA strategy for SPMSMs, the d-axis stator current, i_{sd} is set to zero.

The stator voltage vector for the TPFS inverter-fed PMSM drive is unique and distinct from the conventional TPSS inverter. According to [194] it is given by:

$$\begin{aligned} \mathbf{v}_s = \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} &= \frac{V_{dc1}}{6} \begin{bmatrix} -w_b - w_c - 2 \\ 2w_b - w_c + 1 \\ -w_b + 2w_c + 1 \end{bmatrix} \\ &+ \frac{V_{dc2}}{6} \begin{bmatrix} -w_b - w_c + 2 \\ 2w_b - w_c - 1 \\ -w_b + 2w_c - 1 \end{bmatrix} \end{aligned} \quad (2-18)$$

where w_b and w_c are switching functions defined as follows:

$$w_j = \begin{cases} 1, S_j \text{ closed} \\ -1, \bar{S}_j \text{ closed} \end{cases} \quad j = b, c \quad (2-19)$$

representing the switching states of the four switches. Combining all possible switching states in (2-18), the four basic vectors of the stator voltage in the $\alpha - \beta$ coordinate system are given in Table 2-5 via Clarke's transformation. As witnessed in Table 2-5, the zero vectors which typically occupy the remaining time portions after the active vectors have fulfilled their task within the conventional SVM schemes are non-existent in the TPFS inverters. Consequently, a pair of opposite vectors are utilized to equivalently synthesize the zero vectors, producing extra complexity in the process.

TABLE 2-5 Basic Space Vectors of the TPFS Inverter-fed PMSM Drive

Switching State (w_b, w_c)	v_α	v_β
$V_1(0, 0)$	$2V_{dc2}/3$	0
$V_2(1, 0)$	$(V_{dc2} - V_{dc1})/3$	$(V_{dc1} + V_{dc2})/\sqrt{3}$
$V_3(1, 1)$	$-2V_{dc1}/3$	0
$V_4(0, 1)$	$(V_{dc2} - V_{dc1})/3$	$-(V_{dc1} + V_{dc2})/\sqrt{3}$

2.4.4 Analysis of the SVM of the TPFS Inverter

The fundamental concept of SVM in a TPFS inverter is identical to that of the TPSS inverter, where the reference voltage vector is synthesized by two neighbouring active (basic) vectors per the principle of the voltage-second value being equal. Nevertheless, the primary obstacle as far as the modulation within a TPFS is concerned is the synthesis of the equivalent zero vector, which is directly related to the performance of the modulation scheme. Typically, two opposite vectors, either $(V_1 - V_3)$ or $(V_2 - V_4)$, whose voltage integral equates to zero, can be used to synthesize the zero vectors. For instance, in a scenario where the reference voltage v_s lies in Sector I, the effective portion is always synthesized by V_1 and V_2 , whereas the remaining segment can be synthesized by either $V_1 - V_3$ or $V_2 - V_4$, as depicted in Fig. 2-29. In the SVM(A) approach shown in Fig. 2-29 (a), the equivalent zero vectors are synthesized by $V_1 - V_3$, hence the reference vector v_s is synthesized by V_1 , V_2 and V_3 . On the other hand, in the SVM(B) method depicted in Fig. 2-29 (b), the equivalent zero vectors are synthesized by $V_2 - V_4$, thus v_s is synthesized by V_1 , V_2 and V_4 . For the sake of simplicity, the capacitor voltages are assumed to be identical ($V_{dc1} = V_{dc2} = V_{dc}/2$). Based on the zero vector synthesis procedures, two kinds of SVM method are provided giving rise to two switching sequences as follows: SVM(A): $V_1 - V_2 - V_3 - V_2 - V_1$ and SVM(B): $V_2 - V_1 - V_4 - V_1 - V_2$. Consequently, out of the four basic vectors, three should be adopted for the synthesis. In instances where the reference vector, v_s lies in other sectors, the three utilized vectors in the two SVM algorithms are listed in Table 2-6.

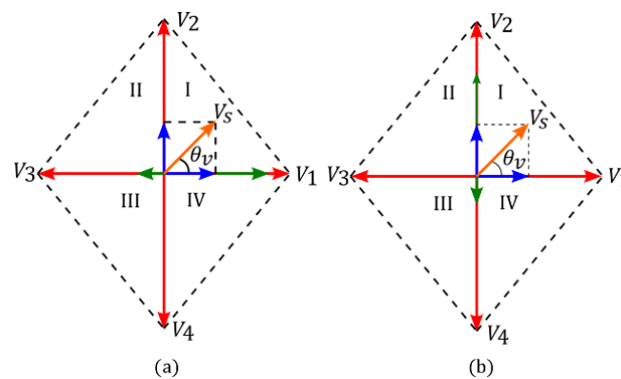


Fig. 2-29. Space vector synthesis in TPFS Inverter-fed PMSM drives. (a) utilizing $V_1 - V_3$ to synthesize zero vectors [SVM(A)]. (b) utilizing $V_2 - V_4$ to synthesize zero vectors [SVM(B)] [194].

TABLE 2-6 Vectors used in the Various Sectors for the Two SVM Strategies

SVM STRATEGY	Sector I	Sector II	Sector III	Sector IV
SVM(A)	V_1, V_2 and V_3	V_1, V_2 and V_3	V_1, V_3 and V_4	V_1, V_3 , and V_4
SVM(B)	V_1, V_2 and V_4	V_2, V_3 and V_4	V_2, V_3 and V_4	V_1, V_2 and V_4

The duration times per switching period can be calculated once the utilized vectors are determined. The duration times are calculated by

$$V_1T_1 + V_2T_2 + V_3T_3 + V_4T_4 = v_sT_s \quad (2-20)$$

$$T_1 + T_2 + T_3 + T_4 = T_s \quad (2-21)$$

where v_s refers to the reference stator voltage vector, T_s represents the total switching period and V_n ($n = 1, 2, 3, 4$) denotes the active voltage vectors available for synthesis of zero voltage vectors and T_n ($n = 1, 2, 3, 4$) is the duration times of the active voltage vectors. Since only three vectors are utilized per switching period, one of the vector durations is equal to zero. For instance, T_4 is equal to zero when utilizing the SVM(A) strategy in sectors I and II. Likewise, T_1 is equal to zero when utilizing SVM(B) in sectors II and III. The switching sequences based on (2-20) and (2-21) are shown in Fig. 2-30 (a) & (b) (with only half of the switching period shown). By analyzing Fig. 2-30 (a) & (b), the active portions of the space vectors in both SVM approaches are identical (for V_1 and V_2). However, because portions of V_1 and V_2 are used for zero vector synthesis in SVM(A) and SVM(B), respectively, the durations and allocations of V_1 and V_2 differ in the two SVM algorithms. Compared to V_1 and V_2 , the use of V_3 and V_4 stands out in SVM(A) and SVM(B) because of the distinct zero vector synthesis approaches, resulting in completely different switching sequences for the two SVM algorithms. As a result of this, the performances of both SVM strategies are primarily influenced by the presence of the equivalent zero vectors [195].

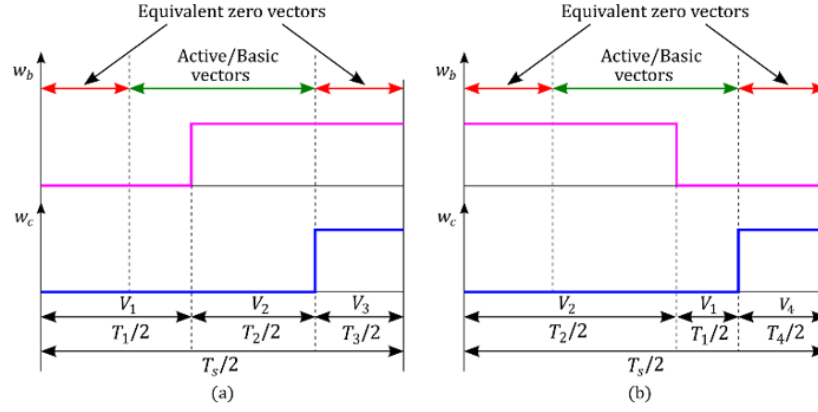


Fig. 2-30. Switching sequence of TPFS Inverter-fed PMSM drives under (a) SVM(A) strategy. (b) SVM(B) strategy [195].

2.4.5 Impact of the Utilized SVM algorithm on the RMS Values of the Torque Ripples

It should be noted that the SVM strategies only differ in their switching sequences; their duty ratios per switching period are identical, regardless of the zero vector synthesis approach. Hence, they can eliminate second-order torque ripples caused by capacitor voltage fluctuations. However, the various switching sequences provide distinct stator voltage harmonic contents, leading to completely different torque harmonics. In a TPFS inverter-fed PMSM drive, an error exists between the instantaneous applied voltage vector and the reference stator voltage vector. As a result of the different SVM approaches, the stator voltages are not purely sinusoidal; they are corrupted with various high frequency harmonic contents, resulting in different levels of torque harmonics. Furthermore, based on the different SVM strategies, the error voltage vectors are distinct corresponding to the utilized equivalent zero vectors, which results in different performances of torque ripples [195]. Consequently, the SVM strategies for TPFS inverter-fed PMSM drives should be evaluated for suppression of torque ripples.

To show the relationship between the torque ripples and the utilized voltage vectors, the differential equation of the electromagnetic torque is deduced from (2-11):

$$\frac{dT_e}{dt} = \frac{3p_n}{2} \left(\frac{d\lambda_s}{dt} i_s + \lambda_s \frac{di_s}{dt} \right) \quad (2-22)$$

$$= \frac{3p_n}{2} \left[(v_s - Ri_s)i_s + \frac{\lambda_s}{L_s} \left(v_s - Ri_s - \frac{d\lambda_f}{dt} \right) \right]$$

Neglecting the stator resistance, (2-22) can be simplified as follows:

$$\begin{aligned} \frac{dT_e}{dt} &= \frac{3p_n}{2} \left[v_s i_s + \frac{1}{L_s} (L_s i_s + \lambda_f) \left(v_s - \frac{d\lambda_f}{dt} \right) \right] \\ &= \frac{3p_n}{2L_s} \left(\lambda_f v_s - \lambda_s \frac{d\lambda_f}{dt} \right) \\ &= \frac{3p_n}{2L_s} \left(\lambda_f v_s - \int v_s dt * \frac{d\lambda_f}{dt} \right) \end{aligned} \quad (2-23)$$

The rotor flux, λ_f can be considered constant within a small duration, hence (2-23) can be simplified further to

$$\frac{dT_e}{dt} = \frac{3p_n}{2L_s} \lambda_f v_s \quad (2-24)$$

According to (2-24), the torque ripple caused by the error voltage vectors is defined as follows:

$$\varepsilon_T = T_e - T_e^* = \frac{3p_n}{2L_s} \int \lambda_f (v_s - v_s^*) dt \quad (2-25)$$

where T_e represents the real torque, T_e^* is the reference torque, v_s is the actual stator voltage vector and v_s^* is the reference stator voltage vector, respectively. Inspection of (2-25) depicts an interaction between the rotor flux and the error voltage vectors to produce torque ripples in TPFS inverter-fed PMSM drives. With distinct equivalent zero vectors, the error voltage vectors and their durations differ in the SVM(A) and SVM(B) strategies. Since the torque ripple, upon further scrutiny of (2-25) is the time integral of the cross product result of the rotor flux and the error voltage vector, the two SVM algorithms produce completely different torque ripple wave patterns as shown in Fig. 2-31 (a) & (b).

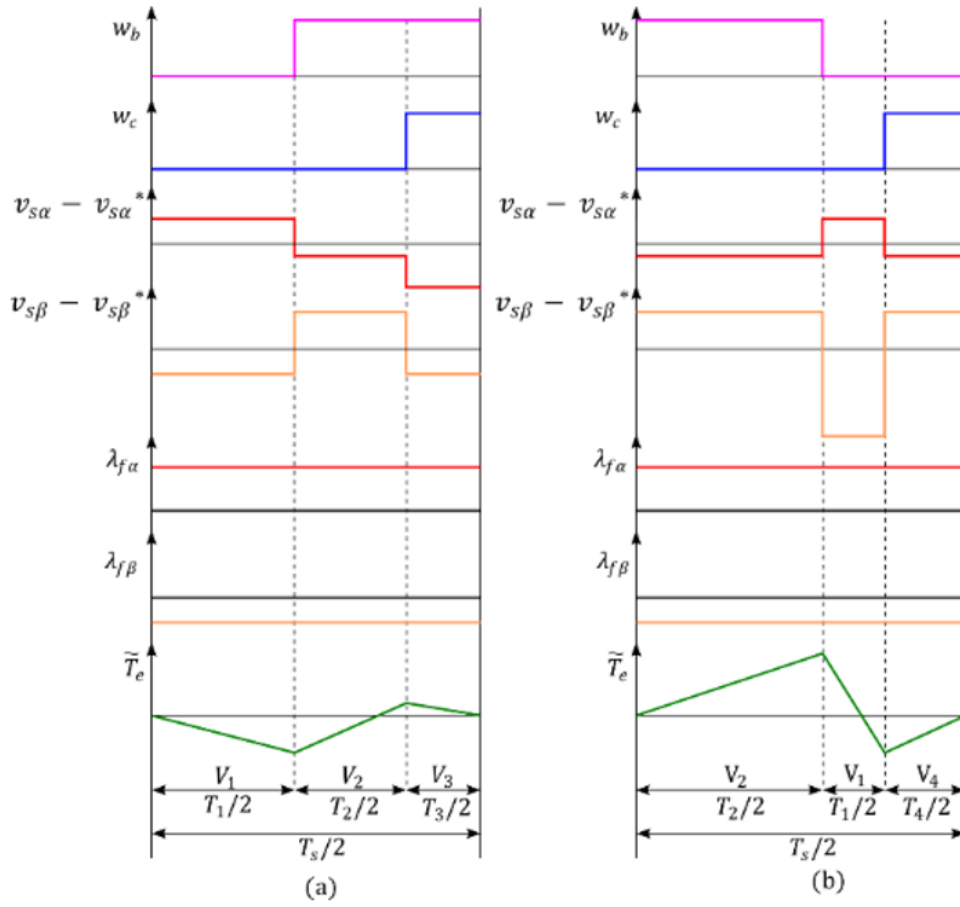


Fig. 2-31. Torque ripples in sector I caused by (a) SVM(A) strategy. (b) SVM(B) algorithm [194].

Based on (2-25), torque ripples in Sector I within a switching period are generated when utilizing the two SVM schemes.

$$\varepsilon_{T1} = \begin{cases} \frac{3p_n}{2L_s} [\lambda_f(V_1 - v_s^*)]t, & 0 < t < \frac{T_1}{2} \\ \frac{3p_n}{2L_s} \{ [\lambda_f(V_2 - v_s^*)] \left(t - \frac{T_1}{2} \right) + \frac{\lambda_f(V_1 - v_s^*)T_1}{2} \}, & \frac{T_1}{2} < t < \frac{T_1 + T_2}{2} \\ \frac{3p_n}{2L_s} [\lambda_f(V_3 - v_s^*)] \left(t - \frac{T_s}{2} \right), & \frac{T_1 + T_2}{2} < t < \frac{T_s}{2} \end{cases} \quad (2-26)$$

$$\varepsilon_{T2} = \begin{cases} \frac{3p_n}{2L_s} [\lambda_f(V_2 - v_s^*)]t, & 0 < t < \frac{T_1}{2} \\ \frac{3p_n}{2L_s} \{[\lambda_f(V_1 - v_s^*)] \left(t - \frac{T_2}{2}\right) + \frac{\lambda_f(V_2 - v_s^*)T_2}{2}\}, & \frac{T_2}{2} < t < \frac{T_1 + T_2}{2} \\ \frac{3p_n}{2L_s} [\lambda_f(V_4 - v_s^*)] \left(t - \frac{T_s}{2}\right), & \frac{T_1 + T_2}{2} < t < \frac{T_s}{2} \end{cases} \quad (2-27)$$

where

$$\begin{aligned} v_s^* &= |v_s^*|(\cos\theta_v + j \sin\theta_v) \\ &= \omega_r \sqrt{\lambda_f^2 + (L_s T_e / 1.5 p_n \lambda_f)^2} (\cos\theta_v + j \sin\theta_v) \end{aligned} \quad (2-28)$$

$$\begin{aligned} \lambda_f &= \lambda_f(\cos\theta_r + j \sin\theta_r) \\ &= \lambda_f \left[\cos\left(\theta_v - \delta - \frac{\pi}{2}\right) + j \sin\left(\theta_v - \delta - \frac{\pi}{2}\right) \right] \end{aligned} \quad (2-29)$$

To minimize the torque ripples within the TPFS inverter-fed PMSM drives, the tendencies of the two SVM strategies with respect to torque ripple production ought to be numerically examined. Consequently the RMS torque ripple proposed in [196] and [197], which is the cumulative RMS value of all harmonic torques is utilized as a benchmark for the analysis. Within the time domain, the RMS torque ripple is defined as follows:

$$\varepsilon_{TRMS} = \sqrt{\frac{1}{T} \int_0^T \tilde{T}_e^2 dt} \quad (2-30)$$

where $\tilde{T}_e$ represents the difference between the actual torque T_e and the reference torque T_e^* , over a switching period T . From (2-28), a case study within a switching period can be developed considering the symmetry

$$\varepsilon_{TRMS} = \sqrt{\frac{2}{T_s} \int_0^{T_s/2} \tilde{T}_e^2 dt} \quad (2-31)$$

Substituting (2-26) - (2-29) into (2-31) and putting the situations in the other sectors into consideration, the analytical expressions of the RMS torque ripples utilizing SVM(A) and SVM(B) are derived as follows:

$$\begin{aligned}
\varepsilon_{TRMS1} = & \frac{\sqrt{3}p_n\lambda_f T_s}{24V_{dc}L_s} \{27\omega_r^4\lambda_f^4[-8\cos^4(\theta_v - \delta)] \\
& + 10\cos^2(\theta_v - \delta) + 1\} - 6\sqrt{3}\omega_r^3\lambda_f^3V_{dc}|\sin(\theta_v - \delta)| \\
& [4\cos^4(\theta_v - \delta) - 7\cos^2(\theta_v - \delta) - 3] + 9\omega_r^2\lambda_f^2V_{dc}^2 \\
& [4\cos^4(\theta_v - \delta) - 7\cos^2(\theta_v - \delta) + 1] + V_{dc}^4\cos^2(\theta_v - \delta)\}^{\frac{1}{2}}
\end{aligned} \tag{2-32}$$

$$\begin{aligned}
\varepsilon_{TRMS2} = & \frac{p_n\lambda_f T_s}{8V_{dc}L_s} \{9\omega_r^4\lambda_f^4[-8\cos^4(\theta_v - \delta) + 10\cos^2(\theta_v - \delta) + 1] \\
& - 18\omega_r^3\lambda_f^3V_{dc}|\cos(\theta_v - \delta)|^3 [(4\cos^2(\theta_v - \delta) - 3) + V_{dc}^4\sin^2(\theta_v - \delta)] \\
& + 3\omega_r^2\lambda_f^2V_{dc}^2 [12\cos^4(\theta_v - \delta) - 9\cos^2(\theta_v - \delta) - 2]\}^{\frac{1}{2}}
\end{aligned} \tag{2-33}$$

According to (2-32) and (2-33), the RMS torque ripple over a switching period is dependent on the position of the stator voltage vector and the particular SVM algorithm utilized.

2.5 Literature Review of the State-of-the-art in Mitigating Errors in EV Powertrain Components

The performance, reliability, and safety of EV powertrains are fundamentally constrained by the presence of non-idealities across their constituent components. Modern research has therefore focused on identifying, modelling, and mitigating errors arising from power electronic converters, electric machines, sensing systems, and embedded control platforms. In parallel, fault-tolerant control strategies have been developed to ensure continued operation under degraded conditions. This section presents a synthesis of the current state of the art, with emphasis on mitigation techniques and their limitations.

2.5.1 Inverter-Induced Errors and Compensation Strategies

Power electronic inverters are a primary source of distortion in EV powertrains due to their inherently nonlinear switching behaviour. Practical inverters exhibit dead-time effects, semiconductor voltage drops, and propagation delays, all of which introduce discrepancies between the commanded and actual output voltages. These discrepancies distort phase currents, increase harmonic content, and lead to torque ripple in electric machines [198]. The impact is

particularly pronounced in high-performance PMSM drives, where precise current control is essential for smooth torque production.

To mitigate these effects, several compensation strategies have been proposed. Pulse-based dead-time compensation techniques adjust switching signals directly to counteract timing mismatches [199], while average voltage compensation methods estimate the effective voltage error introduced by dead-time and correct it within the control loop [200]. Observer-based approaches have also gained traction, where inverter nonlinearities are treated as disturbances and estimated using state observers, allowing real-time compensation without additional hardware [198]. Furthermore, harmonic suppression algorithms have been developed to attenuate specific frequency components associated with inverter-induced distortions [201], thereby improving current waveform quality.

The emergence of wide-bandgap semiconductor devices, such as silicon carbide (SiC) and gallium nitride (GaN), has introduced both opportunities and challenges. While these devices enable higher switching frequencies and improved efficiency, they also exacerbate issues such as electromagnetic interference and switching transients, which can introduce new forms of measurement noise and control instability [202]. Consequently, modern compensation strategies increasingly incorporate high-bandwidth control and filtering techniques to address these high-frequency effects.

2.5.2 Electric Machine Non-Idealities and Robust Control Approaches

Electric machines, particularly PMSMs, are subject to various sources of uncertainty that degrade performance. Parameter variations arising from temperature changes, magnetic saturation, and ageing affect key machine constants such as resistance, inductance, and flux linkage. These variations introduce modelling inaccuracies that compromise the effectiveness of model-based control strategies [203].

Nonlinear magnetic effects further complicate system behaviour, especially under high load conditions where saturation becomes significant. In addition, rotor eccentricities, whether static, dynamic, or mixed lead to air-gap asymmetries, resulting in unbalanced magnetic pull and the generation of torque harmonics. These phenomena contribute to increased vibration, acoustic noise, and mechanical stress, ultimately affecting system reliability [204], [205].

To address these challenges, robust control strategies have been widely explored. Sliding mode control (SMC) is particularly notable for its insensitivity to parameter variations and external disturbances, making it well suited for uncertain environments [206]. Disturbance observers have also been employed to estimate and compensate for unmodelled dynamics, thereby enhancing control accuracy [207].

More recently, data-driven and machine learning-based techniques have been introduced to capture complex nonlinear behaviours that are difficult to model analytically. These approaches leverage large datasets to learn system dynamics and provide improved estimation of machine states and parameters. While promising, their application in safety-critical automotive systems remains an active area of research due to concerns related to interpretability and real-time implementation [208].

2.5.3 Sensor Errors and Measurement Uncertainty Mitigation

Accurate sensing is essential for the effective operation of EV powertrains, yet sensors themselves are a significant source of error. Current sensors are affected by offset and gain mismatches, while rotor position sensors, such as resolvers, exhibit amplitude imbalance, phase shift, and conversion inaccuracies within resolver-to-digital converters (RDCs). These errors propagate into the control loop, leading to distorted current regulation and increased torque ripple.

Analog-to-digital converters (ADCs) and associated signal conditioning circuits introduce additional uncertainties, including quantisation noise, nonlinearities, and reference voltage fluctuations. These effects degrade signal fidelity and contribute to control inaccuracies.

To mitigate current sensor-related errors, various calibration and estimation techniques have been proposed. Offline calibration methods aim to correct systematic errors prior to operation, while online calibration techniques adaptively compensate for time-varying inaccuracies during runtime. Observer-based approaches have also been widely used to reconstruct true system states from noisy measurements, thereby reducing reliance on physical sensors [209].

Advanced signal processing methods, including filtering and harmonic compensation, are employed to reduce noise and suppress measurement-induced distortions. In addition, redundancy-based approaches—either through additional sensors or analytical estimation—provide fault detection and isolation capabilities, enhancing system reliability [210].

To counter position sensor errors, algorithms that have been put forward include extremum-seeking compensation strategies [211] and low-order harmonic suppression approaches [212].

2.5.4 Microcontroller and Digital Implementation Effects

The digital implementation of control algorithms introduces a distinct class of errors associated with sampling, quantisation, and discretisation. Finite resolution in ADCs leads to quantisation noise, while limited numerical precision in microcontrollers introduces rounding errors. Sampling delays and asynchronous timing between sensing and actuation further contribute to phase lag within the control loop.

These effects can degrade system stability, particularly in high-speed applications where precise timing is critical. Discretisation of continuous-time control laws may also lead to performance discrepancies if not properly designed.

To address these issues, research has focused on improving digital control architectures through high-speed processors, optimised sampling strategies, and advanced discretisation techniques. Compensation methods, such as delay prediction and digital filtering, are employed to minimise the impact of sampling and computation delays [213], [214]. Additionally, co-design approaches that jointly consider hardware and control algorithm design have been proposed to ensure optimal system performance.

2.5.5 Fault-Tolerant Operation and Sensorless Control

Maintaining system operation in the presence of component failures is a critical requirement for EV safety. Sensorless control techniques have been widely developed to address rotor position sensor failures. These methods rely on observers to estimate rotor position and speed based on electrical measurements, enabling continued operation without physical sensors.

However, sensorless approaches face significant challenges, particularly at low speeds where back-electromotive force signals are weak. To overcome these limitations, hybrid strategies that combine sensor-based and sensorless control have been proposed. These approaches allow seamless transition between modes, ensuring stable operation across a wide speed range.

Fault-tolerant inverter topologies and reconfiguration strategies have also been explored to maintain operation under power electronic failures. These methods often involve modifying switching patterns or redistributing load among available components.

In multi-motor systems, redundancy plays a crucial role in fault tolerance. Cross-referencing information between motors enables fault detection and compensation, enhancing overall system robustness.

2.5.6 Mitigation of CMEs in Electric Drives

Single-Motor Systems

In single-motor drives, CMEs and delays have been addressed using a range of techniques, including offline detection methods, observer-based estimation, harmonic suppression strategies, and topology-based approaches. Offline methods provide baseline calibration, while observer-based techniques enable real-time correction by estimating true current values.

Harmonic suppression methods focus on eliminating distortion components introduced by CMEs, whereas topology-based approaches exploit inverter switching states to improve current reconstruction accuracy. More recently, adaptive filtering techniques have emerged as a powerful solution, enabling dynamic compensation of measurement errors and delays without interrupting control operation.

The effectiveness of these techniques is influenced by the choice of control strategy. Field-oriented control (FOC), direct torque control (DTC), and model predictive current control (MPCC) each present different trade-offs in terms of sensitivity to measurement errors, computational complexity, and dynamic response. MPCC, in particular, offers advantages in handling constraints and incorporating predictive error compensation, making it well suited for adaptive filtering applications.

Multi-Motor Systems

In multi-motor EV powertrains, particularly in quad-motor configurations, CMEs present significantly greater challenges. Errors that are manageable in single or dual-motor systems become compounded due to interactions between multiple drive units. This leads to amplified torque ripple, oscillations, and instability in power distribution.

The literature indicates that while torque vectoring and coordinated control have been extensively studied, relatively limited attention has been given to the systematic calibration of errors across multiple motors. Existing approaches often fail to address the distributed nature of errors or provide real-time correction without disrupting system operation.

Emerging trends focus on distributed calibration strategies and correlative correction methods that leverage interactions between motors to identify and compensate for errors. These approaches aim to maintain synchronisation and ensure consistent torque production across all drive units.

Sensor Fault Detection and Hybrid Control in Dual-Motor Systems

In dual-motor EV configurations, rotor position sensor failure presents a critical challenge. State-of-the-art approaches rely on observer-based estimation techniques to reconstruct rotor position in the event of sensor failure. However, ensuring stability during the transition from sensor-based to sensorless operation remains a key difficulty.

Hybrid control strategies have been developed to address this issue, combining measured and estimated signals through weighted blending techniques. This allows for a gradual transition between modes, reducing transient disturbances and maintaining torque continuity.

Redundant compensation strategies, including cross-checking between motors, have also been proposed. In such approaches, the healthy motor serves as a reference for validating the estimated states of the faulty motor. Additionally, virtual sensing techniques based on d-q axis current analysis enable the detection and compensation of sensor faults without additional hardware.

These methods represent the current state of the art in ensuring fault-tolerant operation in dual-motor systems, although challenges remain in achieving robustness under all operating conditions.

2.5.7 Research Gaps and Motivation

Despite the significant progress reported in the literature on mitigating errors in EV powertrain components, several critical limitations remain. These gaps are particularly evident when considering the integrated, multi-component, and safety-critical nature of modern electric propulsion systems. The research presented in this thesis is motivated by three key areas where

existing approaches remain insufficient, each corresponding to the focus of Chapters 3, 4, and 5.

A. Integrated and Adaptive Mitigation of Hybrid Errors in Single-Motor Drives (Chapter 3 Motivation)

A substantial portion of existing research has focused on mitigating individual error sources within electric drives, such as inverter nonlinearities, current measurement inaccuracies, and computational delays. While effective in isolation, these approaches often fail to account for the simultaneous and interacting nature of errors in practical EV powertrains. In real-world operation, inverter-induced distortions, sensor errors, and digital implementation effects coexist and collectively influence system performance through tightly coupled feedback loops.

Furthermore, many existing compensation techniques, including offline calibration and fixed-parameter harmonic suppression methods, lack the ability to adapt to time-varying operating conditions. This limitation is particularly critical in EV applications, where load conditions, temperature, and switching dynamics continuously change. Observer-based approaches and topology-driven methods offer improvements, but they often rely on accurate system models and may introduce additional computational complexity or require modifications to the control structure.

Another important limitation lies in the integration of error mitigation within advanced control frameworks. Although predictive control strategies, such as model predictive current control (MPCC), offer superior dynamic performance, they are highly sensitive to measurement errors and delays. Current literature provides limited solutions that embed adaptive error compensation directly within predictive control schemes without compromising real-time performance.

These limitations highlight the need for a unified and adaptive framework capable of mitigating hybrid errors in real time while maintaining compatibility with high-performance control strategies. This gap directly motivates the development of the enhanced adaptive filtering and harmonic annulation approach presented in Chapter 3.

B. Distributed and Scalable Error Mitigation in Multi-Motor (Quad-Motor) EV Powertrains (Chapter 4 Motivation)

The transition from single- and dual-motor configurations to multi-motor architectures, particularly quad-motor EV powertrains, introduces a new layer of complexity in error propagation and system interaction. While existing studies have extensively addressed torque vectoring and coordinated control in multi-motor systems, relatively limited attention has been given to the systematic treatment of current measurement errors across multiple drive units.

In multi-motor configurations, current measurement errors that are manageable in single-motor systems become significantly more problematic due to their compounded and distributed nature. These errors lead to phase current imbalance, loss of synchronisation between motors, and inconsistent torque production. As the number of motors increases, the interaction between subsystems amplifies these effects, resulting in pronounced torque ripple, oscillations, and degradation in overall vehicle stability and performance.

Existing calibration and compensation techniques are generally designed for isolated drive systems and do not scale effectively to multi-motor architectures. In particular, there is a lack of methodologies that enable independent yet coordinated calibration across multiple motors, while maintaining real-time operation and avoiding disruption to control loops. Moreover, current approaches do not fully exploit the inherent interconnections between motors that could be leveraged for improved error detection and correction.

These limitations point to the need for distributed and correlative error mitigation strategies that can operate across multiple drive units in a coordinated manner. This gap motivates the development of the real-time correlative correction framework for quad-motor EV powertrains presented in Chapter 4.

C. Robust Fault-Tolerant Control and Seamless Sensor Failure Management in Dual-Motor Systems (Chapter 5 Motivation)

Ensuring reliable operation under sensor failure conditions remains a critical challenge in EV powertrains, particularly in dual-motor configurations where coordination between drive units is essential. While sensorless control techniques have been widely developed to address rotor position sensor failures, their practical implementation is constrained by several limitations.

One of the most significant challenges lies in achieving a smooth and stable transition between sensor-based and sensorless operation. Existing methods often rely on abrupt switching or loosely coupled estimation strategies, which can introduce transient disturbances, torque ripple,

and instability. This issue is exacerbated in dual-motor systems, where asynchronous transitions between motors can compromise overall system performance.

In addition, sensorless estimation techniques are inherently sensitive to operating conditions, with reduced accuracy at low speeds and under parameter uncertainties. Although hybrid control strategies have been proposed to combine measured and estimated signals, the design of robust blending mechanisms that ensure seamless operation across all conditions remains an open problem.

A further limitation in the literature is the underutilisation of inter-motor redundancy and cross-coupling information. In dual-motor EV systems, the availability of multiple drive units presents an opportunity to enhance fault detection and estimation accuracy. However, existing approaches rarely exploit the speed and position feedback from a healthy motor to improve observer convergence and estimation accuracy in a faulty motor, particularly during position sensor failure events.

Moreover, while virtual sensing techniques based on d–q axis current analysis have shown promise in detecting and compensating for sensor faults, their integration within a comprehensive fault-tolerant control framework remains limited.

These gaps highlight the need for integrated fault-tolerant control strategies that combine robust observer design, adaptive blending between control modes, and effective utilisation of cross-motor information. This motivates the development of the hybrid sensor-based and sensorless control framework with enhanced observer convergence and seamless transition capability presented in Chapter 5.

Fig. 2-32 depicts the conceptual flow of the thesis, detailing the sources of error from the selected powertrain components, their impact in closed-loop operation, limitations in existing work and the kind of solutions this dissertation proposes to counteract those constraints.

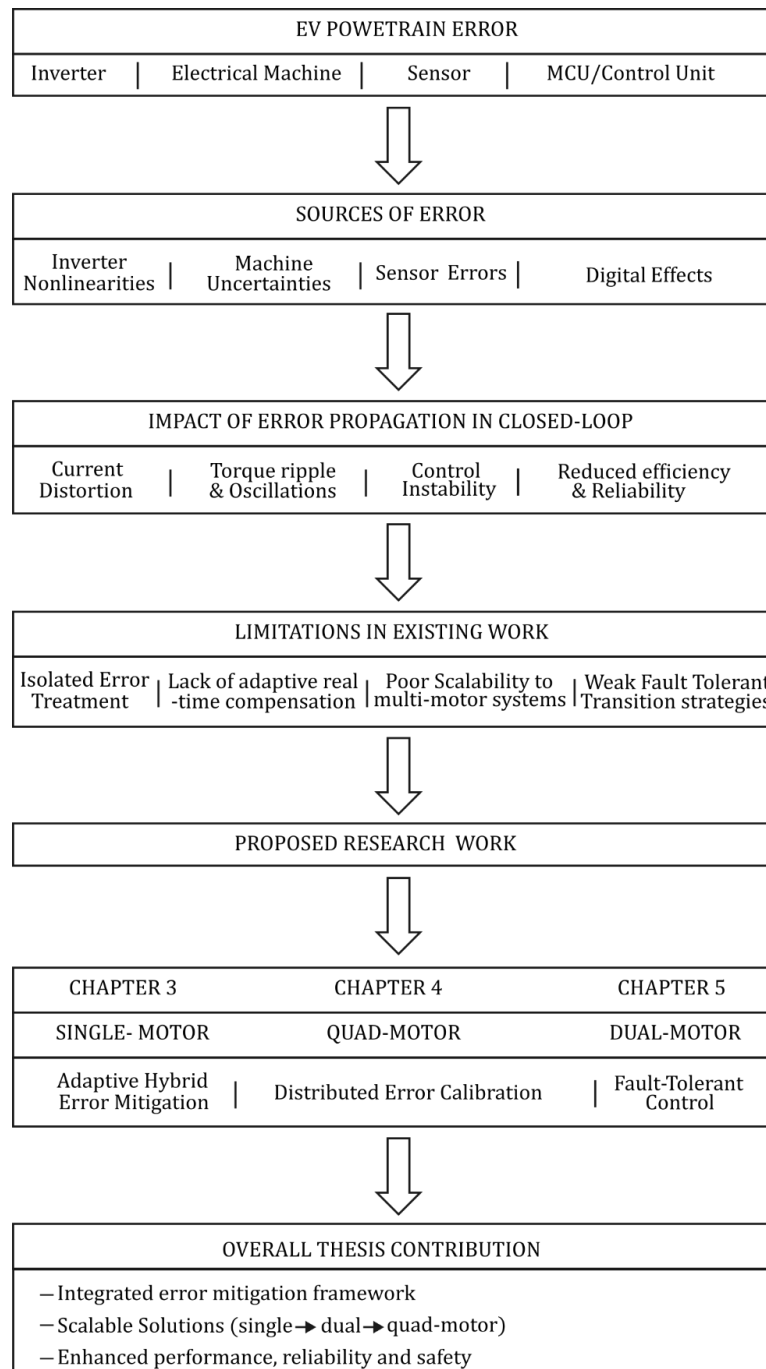


Fig. 2-32. Schematic of Thesis Framework and Research Contribution.

2.6 Summary

This chapter has presented a comprehensive review of EV powertrains, with particular emphasis on the evolving understanding of errors and their impact on system-level performance. The review demonstrates that modern EV systems are no longer treated as

isolated components, but as highly integrated electro-mechanical systems in which interactions between subsystems significantly influence overall behaviour. A key insight from the literature is that errors originating from sensing, power electronics, and machine dynamics do not remain localised; rather, they propagate through tightly coupled control loops, often amplifying their impact on torque production, stability, and efficiency.

The chapter has also examined the principal sources of such errors, including those arising from power electronic inverters, analog-to-digital conversion, position sensing (resolvers), electric machines, and current sensors. While various compensation and mitigation techniques have been proposed in the literature, many approaches remain component-specific and fail to address the compounded and interacting nature of errors in integrated drive systems. This limitation becomes more pronounced as EV architectures evolve from single-motor to multi-motor configurations, where error propagation across multiple drive units introduces additional complexity and performance degradation. Overall, the chapter establishes that as EV systems continue to evolve toward higher levels of integration and multi-motor configurations, managing error propagation becomes a fundamental challenge. This underscores the need for more holistic, system-oriented approaches to analysis, modelling, and control, forming the foundation for the investigations presented in the subsequent chapters.

Chapter 3 Suppression of SPMSM-Based Powertrain Hybrid Errors Using Adaptive Filters Integrated within FCS-MPC Controllers

This chapter proposes an enhanced adaptive filtering-based control strategy for suppressing hybrid errors in SPMSM-driven powertrains within a Finite Control Set Model Predictive Current Control (FCS-MPCC) framework. Hybrid errors arising from current measurement inaccuracies and control delays introduce harmonic distortions in dq-axis currents, leading to torque ripple and speed oscillations. An Adaptive Selective Harmonic Annulation (ASHA) algorithm is first employed to mitigate speed ripple by compensating q-axis current harmonics. However, its inability to address d-axis harmonics limits overall performance. To overcome this limitation, an Enhanced ASHA (E-ASHA) scheme is developed, enabling simultaneous compensation of both d- and q-axis harmonic components. This results in comprehensive suppression of current distortions and effective elimination of speed ripple without altering the existing control structure.

The proposed E-ASHA is integrated within the FCS-MPCC framework, providing adaptive, real-time harmonic estimation and compensation under varying operating conditions. Experimental validation on a 1 kW SPMSM drive demonstrates that the proposed E-ASHA-FCS-MPCC framework achieves significant harmonic suppression, reducing q-axis current total harmonic distortion (THD) by up to 80.5% at low speeds and maintaining over 46% torque ripple suppression even under high-speed heavy-load conditions while maintaining computational efficiency. Overall, the proposed strategy offers a unified and robust solution for hybrid error suppression, improving drive performance and demonstrating strong potential for application in electric vehicle powertrain systems.

3.1 Introduction

For high-performance PMSM drives, information obtained from sensors is crucial. Feedback signals from position and current sensors form the basis for effective control algorithms within PMSM drive systems. Fundamentally, the speed value calculated by the position sensor is used as the feedback signal for the speed control and can be utilized to generate feedforward

compensation terms for the current control loop [215] or to generate the torque-producing current references [216].

3.1.1 The Dynamics of Sensor, Feedback, and Inverter Delays

With accurate position and current feedback, the control system can optimize the motor's performance, leading to increased efficiency and reduced energy consumption. The accuracy of the control system is compromised when feedback information is delayed. These delays in sensor measurements can lead to errors in position, speed or torque control, affecting the motor's ability to follow reference commands precisely.

The nature of the components utilized within the inner control loop subjects the measurement path to both analog and digital delays. Analog delays are typically caused by inherent characteristics of physical components such as sensors, filters, and amplifiers within the signal transmission path. They can introduce a phase shift between the actual current and the measured current, leading to errors in the feedback loop. These delays primarily affect the accuracy and timeliness of current measurements. If the current signal is delayed due to sensor or conditioning circuit limitations, the system may not have real-time current data, leading to imprecise current estimation. Digital delays, on the other hand, arise from sampling, computation and actuation within digital controllers, including delays from analog-to-digital (ADC) conversion, digital signal processing (DSP), and digital-to-analog (DAC) conversion. Digital delays can be categorized into computation delay and pulse width modulation (PWM) delay [217]. The computation delay is the time duration from the sampling instant to the PWM reference update instant, and it is one sampling period in the synchronous sampling case (where the sampling takes place at the beginning and in the middle of a switching period) [218].

The PWM switching delays, conversely, occur during the switching action (on/off states) of power devices (such as IGBT or MOSFETs). They are caused by the zero-order hold (ZOH) effect which keeps the PWM reference constant after it has been updated [219]. Fast and efficient PWM algorithms are essential to minimize these switching delays. In terms of the dynamic control of the current loop, the modulation and computational delays limit the bandwidth and robustness of the control system because of the introduced phase lag [219]. Such a phase lag tends to reduce the phase margin of the current loop, hence degrading the control system's performance. The combination of offset and scaling errors inherent within analog current sensors coupled with analog delays from signal processing components together

with digital delays lead to the formation of hybrid errors. These hybrid errors result in non-optimal current waveforms, leading to unwanted torque fluctuations and low efficiency.

3.1.2 Error Comparison of Field-Oriented Control and Model Predictive Control Strategies for PMSMs

Since the PMSM drive system consists of several nonlinear components, the use of the conventional Field-Oriented Control (FOC) strategy as an all-purpose suitable control approach leads to unsatisfactory performance within the electric powertrain. The advancement of microcontroller technology has motivated the exploration of more sophisticated nonlinear strategies to regulate electric machines. Among such advanced control methods, the Finite Control Set Model Predictive Control (FCS-MPC) has emerged as an effective alternative to controlling PMSMs due to its merit of high dynamics, easy incorporation of constraints and exceptional simplicity [220]. Out of the various variations of FCS-MPC, Finite Control Set Model Predictive Current Control (FCS-MPCC) has gained significant attention in electric drive applications due to its fast dynamic response, intuitive handling of system constraints, and ability to directly select optimal switching states. However, despite these advantages, its adoption in PMSM-based EV powertrains introduces several risks when compared with the more mature and widely implemented FOC strategy.

One of the primary risks associated with FCS-MPCC is its high sensitivity to model inaccuracies. Unlike FOC, which relies on cascaded control loops with inherent robustness to parameter variations, FCS-MPCC explicitly depends on an accurate mathematical model of the system to predict future states. Any mismatch in machine parameters, inverter characteristics, or load conditions can lead to erroneous predictions, resulting in suboptimal switching decisions. In practical EV applications, where parameters such as stator resistance and inductance vary with temperature and operating conditions, this sensitivity can degrade performance and introduce instability if not properly addressed [221].

Another critical concern is the impact of CMEs and delays. Since FCS-MPCC relies on real-time measurements of currents, voltages, and rotor position to evaluate its cost function, inaccuracies in these signals directly affect prediction accuracy. Errors arising from current sensors, ADC quantisation, or sampling delays can propagate through the predictive model, leading to incorrect switching state selection. Compared to FOC, which benefits from feedback

regulation and filtering within PI control loops, FCS-MPCC lacks inherent smoothing mechanisms, making it more vulnerable to noise and disturbances [222].

A further limitation relates to the variable switching frequency characteristic of FCS-MPCC. Unlike FOC, which typically operates with a fixed switching frequency due to PWM, FCS-MPCC produces a variable switching pattern depending on the optimisation outcome at each sampling instant. This variability complicates the design of electromagnetic interference (EMI) filters and may lead to increased switching losses under certain operating conditions. In safety-critical automotive systems, predictable switching behaviour is often preferred for ease of validation and compliance with standards [223].

The computational burden of FCS-MPCC also presents a practical risk. At each sampling instant, the controller must evaluate a cost function for all possible switching states, which can become computationally intensive, particularly when extended to multi-motor systems or when incorporating additional constraints such as fault tolerance or thermal limits. This requirement places significant demands on the microcontroller or digital signal processor, potentially limiting scalability or requiring more expensive hardware compared to FOC implementations [224].

In addition, FCS-MPCC requires careful cost function design and weighting factor tuning, which introduces another layer of complexity. The performance of the controller is highly dependent on the selection of weighting factors used to balance multiple objectives, such as current tracking, switching minimisation, and torque ripple reduction. Improper tuning can lead to conflicting objectives, degraded performance, or even instability [225]. In contrast, FOC relies on well-established PI tuning methodologies, which are generally more intuitive and easier to implement in industrial settings.

From a fault tolerance perspective, FCS-MPCC can also be more challenging to adapt under degraded conditions. While predictive control frameworks can, in principle, incorporate fault constraints, doing so increases the dimensionality and complexity of the optimisation problem [226]. FOC, on the other hand, benefits from a modular structure that allows easier integration of fault-tolerant strategies, such as current limiting, reconfiguration, or fallback control modes.

Finally, there is a maturity and standardisation risk associated with FCS-MPCC. FOC has been extensively validated over decades of industrial application and is widely supported by commercial drive systems and automotive platforms. In contrast, FCS-MPCC, although

promising, is still an active area of research, with fewer standardised design procedures and less widespread industrial adoption. This can pose challenges in terms of certification, reliability validation, and integration into existing EV control architectures.

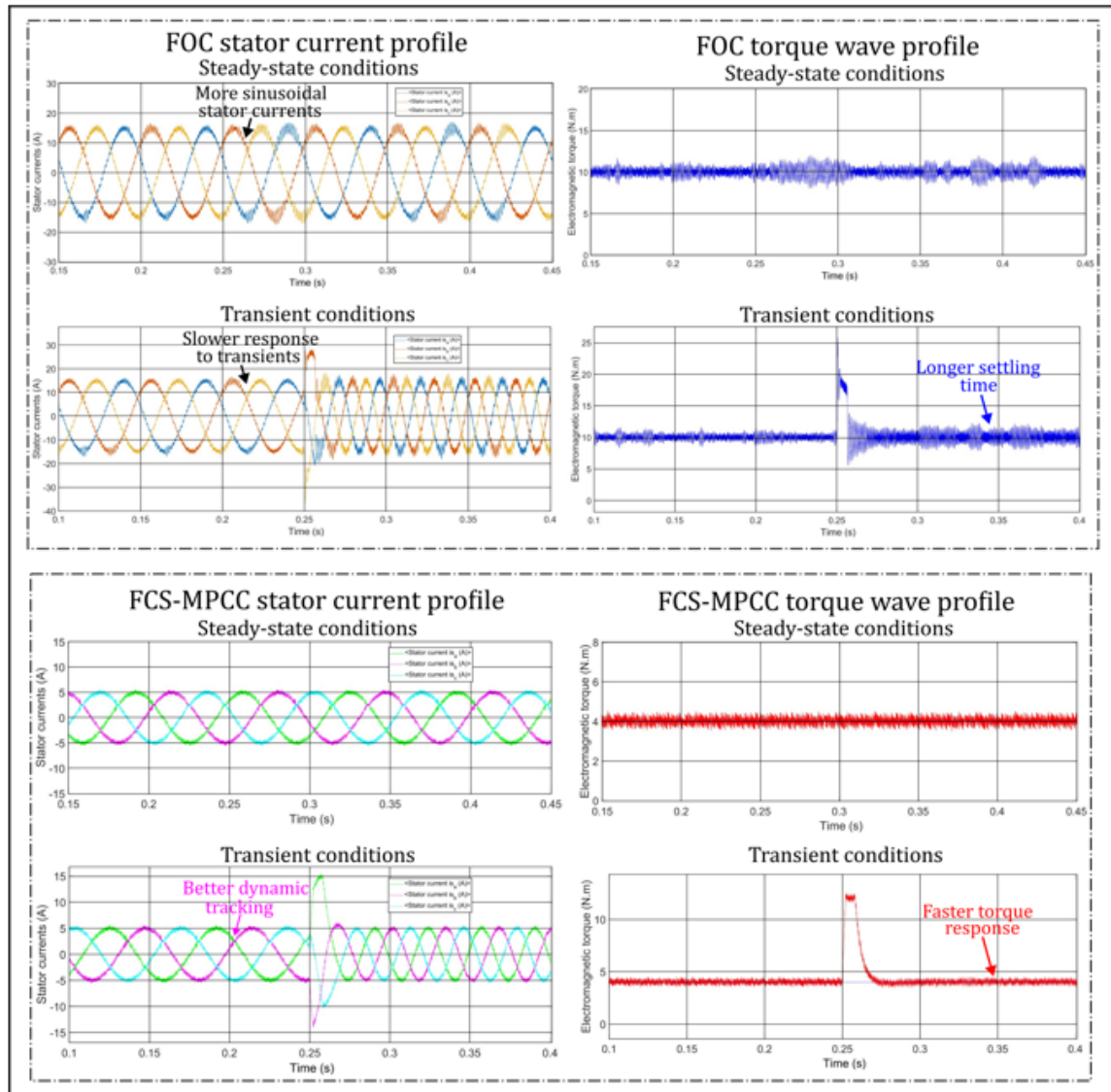


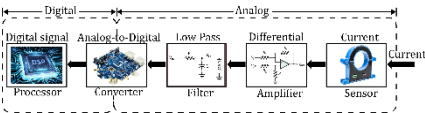
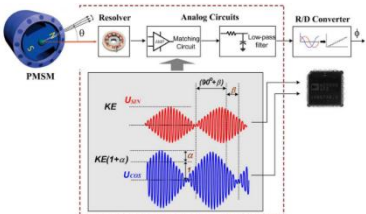
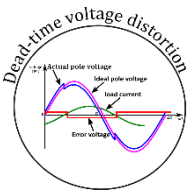
Fig. 3-1. Comparison of FOC and FCS-MPCC at steady-state and transient states highlighting their strengths and weakness.

Sensitivity to errors and quick error detection are more critical for an FCS-MPCC algorithm because it relies on accurate predictions and a finite set of control actions, making it more susceptible to errors and their rapid propagation. In contrast, FOC's continuous control approach and inherent robustness provided by proportional-integral (PI) controllers make it less dependent on rapid error detection to maintain control performance. Fig. 3-1 portrays a

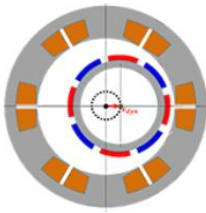
fundamental comparison of stator currents and electromagnetic torque waveforms for FCS-MPCC and FOC at steady-state and transient conditions.

The juxtaposition reveals that FCS-MPCC is more sensitive to errors in both steady-state and transient states. This is primarily due to its reliance on an accurate predictive model and the discrete nature of its control actions, which can lead to greater susceptibility to parameter variations, modelling errors, and external disturbances. Table 3-1 compares how errors from some of the vital powertrain components distinctly affect the two control strategies.

TABLE 3-1 Effect of Errors from Key Powertrain Components on FCS-MPCC and FOC Control Strategies

Error Type	Impact on FCS-MPCC	Impact on FOC
Current Sensor Error 	• Directly affects cost function evaluation, leading to incorrect switching decisions. • Can cause instability due to incorrect predictions of future states.	• Affects PI controllers and current loop tuning. • If undetected, these errors result in improper decoupling of torque and flux control, impacting steady-state and dynamic performance.
Position Sensor Error 	• These errors directly impact rotor angle estimation, affecting transformation to the synchronous reference frame. • This results in inaccurate stator current predictions and suboptimal voltage vector selection, degrading control performance.	• Causes phase misalignment in dq transformation, thus disrupting the decoupling strategy. • Small errors lead to reduced efficiency, while larger errors can cause instability (especially in high-speed applications).
Power Electronic Inverter Error 	• Since FCS-MPCC directly manipulates switching states, inverter non-idealities like dead-time effects and voltage drops distort the predicted model. • The cost function minimization may select incorrect states, leading to higher current ripples and	• Inverter errors introduce voltage disturbances, affecting the PI-based current regulators. • This results in increased harmonic distortion and reduced torque accuracy.

Rotor Eccentricity Error



- Rotor eccentricity causes uneven air gaps, leading to non-sinusoidal flux distributions and harmonics in the machine.
- FCS-MPCC may struggle to accurately predict the system behaviour due to these unmodeled dynamics, resulting in increased current and torque ripple.
- Eccentricity introduces low-order harmonics in the stator current, degrading performance.
- The PI-based regulators partially compensate for small errors but fail for significant eccentricities.

Although FCS-MPCC is inherently sensitive to CMEs and model inaccuracies, its superior dynamic performance and flexibility make it highly attractive for advanced EV powertrain applications. Adaptive filtering techniques are therefore employed not merely as corrective tools but as enabling mechanisms that enhance signal quality and ensure reliable prediction. This synergistic integration is particularly important in PMSM powertrains, where precision in current control directly determines torque quality and system safety.

An essential stage for both predictive and vector control algorithms is the need for the stator currents converted into voltage signals by the sensors to undergo signal conditioning before being digitized. The process involves a significant level of signal filtering which ultimately results in filter delays [227], [228], [229]. Consequently, the calibration precision and the prediction precision (in the case of the MPCC scheme) tend to be compromised, since the measured currents are not in real-time. Moreover, within the MPCC algorithm, at designated instances in time, the stator currents are appropriately detected at the onset of a new control period, however, the selected switching state is held and applied to the drive at the next control period. This one-step delay is due to the inherent updating mechanism of modern microprocessors [230], [231] and it subjects the switching states applied to the drive to suboptimal conditions since they are selected by utilizing prior current and rotor position information. The control performance of the motor drive is forced to undergo significant

degradation, especially for systems with low switching frequency, because of this execution delay.

To resolve the impact of either current sensor errors or delays on the PMSM drive system, a significant level of research has been conducted over the decades. Literatures [232], [233], [234], [235] all tackle the problem from a predictive control point of view. Even though this path leads to impressive results, the complexity, computational demands, and narrow scope of applicability often make the adoption of these strategies less appealing in academic contexts. Other researchers such as [236], [237] have approached the issue from an offline detection standpoint, however, the approach is not cost-effective and requires additional labor and time. The observer-based approaches [96], [98] have massively been used over the years to address the issue, however, these schemes are complex and very intense on the controller. Of the numerous approaches aimed at eradicating the current sensor errors or delay drawbacks, the harmonic suppression methods, specifically, the adaptive filtering strategies, have gained renown due to their effectiveness and robustness.

3.1.3 Review of Adaptive Filtering for Current Measurement Error and Delay Mitigation

The usual strategy for estimating a signal corrupted by additive, undesirable sinusoidal interference is to pass it through a filter that tends to suppress the interference while leaving the signal intact. Adaptive filtering particularly operates on the principle of iteratively adjusting filter coefficients in real time to minimize the difference between a measured (distorted) signal and a desired reference signal. In PMSM drives, this allows the controller to dynamically track and suppress harmonic components or disturbances that arise from current measurement errors, sensor offsets, or delay-induced phase shifts. The filter continuously updates its coefficients based on an adaptation algorithm, commonly the Least Mean Square (LMS) or Recursive Least Squares (RLS) method, so that the mean square of the error between the actual current and its estimated (ideal) value is minimized. As the operating conditions or error characteristics change (for instance, due to load variation or inverter nonlinearity), the adaptive filter reconfigures its response to reject the unwanted harmonic frequencies while preserving the fundamental current component essential for torque production. The LMS algorithm offers a simple gradient-based update mechanism with very low computational complexity, making it well-suited for real-time implementation on embedded digital signal processors in PMSM drive

systems. In contrast, the RLS algorithm achieves faster convergence and superior tracking of rapidly changing disturbances, but at the cost of significantly higher computational burden due to its recursive matrix operations. Consequently, LMS-based adaptive filters are typically preferred in practical PMSM applications, where real-time performance, numerical stability, and implementation simplicity are prioritized over rapid adaptation speed [238], [239], [240].

While the LMS algorithm provides a practical and computationally efficient solution for adaptive filtering in PMSM-based EV powertrains, recent advances in estimation and filtering techniques have introduced alternative approaches that offer improved accuracy under certain conditions, albeit at the expense of increased complexity.

Among these, observer-based techniques have evolved significantly, particularly with the integration of adaptive estimation mechanisms. The Extended Kalman Filter (EKF), and more recently adaptive EKF variants, have been widely adopted for simultaneous estimation of motor states such as rotor position, speed, and electrical parameters [241]. Unlike conventional adaptive filters, adaptive EKF methods dynamically update their error covariance matrices, enabling improved tracking performance in the presence of noise and modelling uncertainties. This capability allows for more accurate estimation and reduced steady-state jitter compared to traditional LMS-based filters, particularly in scenarios where system dynamics are highly nonlinear. However, these advantages come at the cost of increased computational complexity and sensitivity to initialization and modelling assumptions, which can limit their practicality in real-time embedded automotive applications.

In an effort to balance the trade-offs between convergence speed and steady-state accuracy, hybrid adaptive filtering approaches have also been proposed. One notable example is the cascaded LMS–RLS structure, in which a variable step-size LMS algorithm is employed during the initial transient phase to achieve rapid convergence, after which the algorithm transitions to an RLS-based estimator to minimize steady-state error. Such hybrid schemes effectively combine the robustness and simplicity of LMS with the fast convergence and high accuracy of RLS. Despite their improved performance, these approaches introduce additional algorithmic complexity, including switching logic and increased computational burden, which may pose challenges for implementation in high-frequency EV control loops [242].

More recently, data-driven and machine learning-based methods have emerged as promising tools for addressing nonlinear and highly non-stationary disturbances in electric drives.

Techniques such as neural network-based estimators and optimization-driven approaches, including particle swarm optimization, have been explored for parameter estimation and error compensation. These methods are capable of capturing complex system nonlinearities and adapting to varying operating conditions without requiring explicit mathematical models. As a result, they can outperform traditional linear adaptive filtering techniques, such as LMS and RLS, in environments characterized by strong nonlinearities and stochastic disturbances. Nevertheless, their application in EV powertrains remains constrained by several practical considerations, including the need for extensive training data, high computational requirements, and challenges related to interpretability and real-time implementation in safety-critical systems [243], [244].

In comparison to these advanced approaches, the LMS algorithm maintains a distinct advantage in terms of implementation simplicity, numerical stability, and compatibility with embedded control platforms. While it may not achieve the same level of estimation accuracy as adaptive EKF or hybrid LMS–RLS schemes, its ability to operate reliably under real-time constraints makes it particularly suitable for applications where computational resources are limited and deterministic execution is required. Consequently, LMS-based adaptive filtering represents a well-balanced solution for mitigating current measurement errors and delays in PMSM powertrains, especially when enhanced through adaptive step-size tuning and integrated within advanced control frameworks.

Recent studies have applied adaptive filtering to current measurement error (CME) and delay compensation. In [145], an LMS-based approach suppresses sixth-order harmonics caused by inverter dead time; however, it targets a single dominant frequency. The improved ASHE strategy in [245] compensates for dq-axis CMEs without motor parameter identification but requires careful tuning of adaptation gains. In [228], adaptive harmonic elimination and vector reconstruction techniques address both sampling delays and current errors, albeit with increased computational complexity. Similarly, [246] employs adaptive active disturbance rejection control (ADRC) to mitigate uncertain current ripples, though sensitivity to high-frequency noise remains a concern.

Despite these advancements, most existing methods treat measurement errors and control delays separately or are implemented within PI-based control frameworks. Few studies integrate adaptive harmonic suppression directly into predictive current control structures such

as FCS-MPCC. Moreover, unified compensation of multi-harmonic components in both dq axes under hybrid error conditions remains insufficiently addressed.

3.1.4 Motivation and Contributions

To overcome the aforementioned limitations, this chapter proposes a unified hybrid error suppression method that simultaneously compensates for current measurement errors and delay-induced distortions using an Enhanced Adaptive Selective Harmonic Annulation (E-ASHA) algorithm embedded within the FCS-MPCC framework. The algorithm offers unified, real-time compensation for both sensor-induced errors and delay-driven harmonics directly in the dq current domain, achieving precise multi-harmonic suppression.

The main contributions of this chapter are summarized as follows:

- 1) Unified Hybrid Error Suppression without Observers or Extra Sensors: The proposed strategy compensates for both current sensor inaccuracies and control loop delays simultaneously, eliminating the need for complex observer design or hardware augmentation.
- 2) Integration of E-ASHA Algorithm within FCS-MPCC Framework: By embedding the adaptive filter directly into the predictive control loop, the system achieves real-time harmonic suppression based on system feedback, improving torque precision and reducing speed ripple without disrupting the control loop's stability.
- 3) Dual-Axis Harmonic Compensation for Enhanced Torque Control: The ASHA algorithm is extended to both the q-axis and d-axis currents (via an enhanced-ASHA approach), enabling comprehensive suppression of speed ripple and torque distortion, an advancement rarely addressed in existing literature.

The proposed methodology is particularly valuable for electrified transport systems (vehicles, aircraft, and ships) and renewable energy applications, where precision, efficiency, and real-time adaptability are critical.

3.2 SPMSM Model and Model Predictive Current Control

3.2.1 Mathematical Model of the SPMSM

State-space models are well suited for SPMSM MPC applications due to certain unique inherent features they possess which offer them the leverage to exploit common behaviours of multivariable systems. They are represented by at least one differential equation and can reflect the transient behaviours of multivariable systems with precision. The state-space model that describes the electrical and mechanical dynamics of an SPMSM in the synchronous rotating reference frame (dq reference frame) can be represented by the following set of differential equations, where the iron saturation and hysteresis loss are assumed to be negligible [247]:

$$\begin{aligned}\frac{di_d}{dt} &= -\frac{Ri_d}{L} + \omega_e i_q + \frac{u_d}{L} \\ \frac{di_q}{dt} &= -\frac{Ri_q}{L} - \frac{\omega_e(Li_d + \psi_f)}{L} + \frac{u_q}{L} \\ T_e &= \frac{3}{2}P(\psi_f + (L_d - L_q)i_d) i_q\end{aligned}\tag{3-1}$$

$$\frac{d\omega_m}{dt} = \frac{1}{J}(1.5p(\psi_f i_q + (L_d - L_q)i_d i_q) - T_L - B\omega_m)\tag{3-2}$$

where i_d and i_q are the respective currents of the dq-axis, u_d , u_q are the dq-axis control voltages. L represents the stator inductance, R is the stator winding resistance, ω_e is the electrical rotor angular velocity in units of radians per second (rad/s), and ψ_f is the permanent magnet flux linkage. T_e , T_L , ω_m and p are the electromagnetic torque, load torque, rotor mechanical angular speed and the number of pole pairs respectively. Furthermore, J and B represent the moment of inertia and the viscous friction coefficient respectively. The viscous friction coefficient of the system is small enough to be ignored.

To predict the current at the next time interval, the continuous domain model (voltage equation) must be discretized using the forward Euler discretization approach at a time step of T (control period) as follows

$$\begin{cases} i_d(k+1) = \left(1 - \frac{TR}{L}\right) \cdot i_d(k) + T\omega_e i_q(k) + \frac{T}{L} \cdot u_d(k) \\ i_q(k+1) = \left(1 - \frac{TR}{L}\right) \cdot i_q(k) - T\omega_e i_d(k) + \frac{T}{L} \cdot u_q(k) \\ \quad - \frac{T\omega_e \psi_f}{L} \end{cases} \quad (3-3)$$

In the conventional MPCC, each control period includes only one basic voltage vector, hence, according to the current prediction equation (3-3), the predictive current of each basic voltage vector action can be obtained easily. Fig. 3-2 depicts a block diagram of the FCS-MPCC structure, highlighting the impact of the propagation of corrupted signals within the inner control loop. In the figure, the offset, scaling errors and delays introduce inaccuracies in the predictive model, causing the optimizer to minimize a cost function that does not represent the actual system state. This leads to degraded tracking performance and might introduce oscillations or increased switching losses in the power electronic inverter.

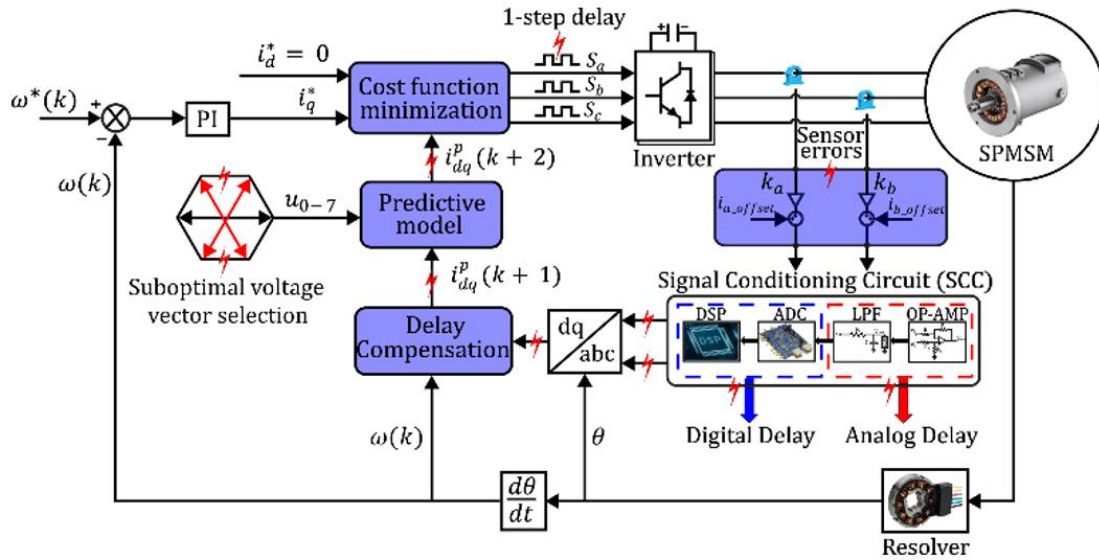


Fig. 3-2. Structure of the FCS-MPCC scheme depicting the impact of the propagation of corrupted signals within the inner loop of the control system.

3.2.2 Delay Compensation

To minimize the negative impact of the one-step delay on the control performance, delay compensation is needed. Based on the measured currents $[i_d(k), i_q(k)]$ and voltages

$[u_d(k), u_q(k)]$, the delay compensated currents can be obtained according to the prediction model (3-3)

$$\begin{aligned} i_d^p(k+1) &= \left(1 - \frac{TR}{L}\right) \cdot i_d(k) + T\omega_e i_q(k) + \frac{T}{L} \cdot u_d(k) \\ i_q^p(k+1) &= \left(1 - \frac{TR}{L}\right) \cdot i_q(k) - T\omega_e i_d(k) + \frac{T}{L} \cdot u_q(k) \\ &\quad - \frac{T\omega_e \psi_f}{L} \end{aligned} \quad (3-4)$$

These compensated currents $i_d^p(k+1)$ and $i_q^p(k+1)$ are employed to replace the measured currents $i_d(k)$ and $i_q(k)$ of the model (3-3), which means that the current prediction model (3-3) can be updated after the one step delay compensation

$$\begin{aligned} i_d(k+2) &= \left(1 - \frac{TR}{L}\right) \cdot i_d^p(k+1) + T\omega_e i_q^p(k+1) + \frac{T}{L} \cdot u_d(k+1) \\ i_q(k+2) &= \left(1 - \frac{TR}{L}\right) \cdot i_q^p(k+1) - T\omega_e i_d^p(k+1) \\ &\quad + \frac{T}{L} \cdot u_q(k+1) - \frac{T\omega_e \psi_f}{L} \end{aligned} \quad (3-5)$$

3.2.3 Cost Function

The predictive current values of the eight voltage vectors after the delay compensation can then be substituted into a cost function g , to evaluate every voltage vector. Then the voltage vector that minimizes the cost function is selected as the optimal one and applied to the SPMSM at the next control period by the inverter [248]

$$g = |i_d^* - i_d(k+2)| + |i_q^* - i_q(k+2)| \quad (3-6)$$

where i_d^* and i_q^* are the d-axis and q-axis reference currents (current commands) respectively, and i_d^* is set to zero and i_q^* is obtained from the output of a speed loop.

3.3 Adaptive Selective Harmonic Annulation (ASHA) Algorithm

The task of eradicating the undesirable harmonic components within the input motor currents can be performed by the ASHA algorithm. Traditionally, the scheme eliminates the harmonics of the selected frequency from the target signal and subsequently outputs the sum of the sinusoidal signals with adaptive weights.

3.3.1 Operational Dynamics of the ASHA Algorithm

The LMS algorithm is used to find the coefficients of the adaptive filter that produces the least mean square of the error signal. It is characterized by parallel computation, online adaptation and simple implementation. The ASHA scheme utilizes the LMS algorithm to update the weights online [249], and its structure is depicted in Fig. 3-3.

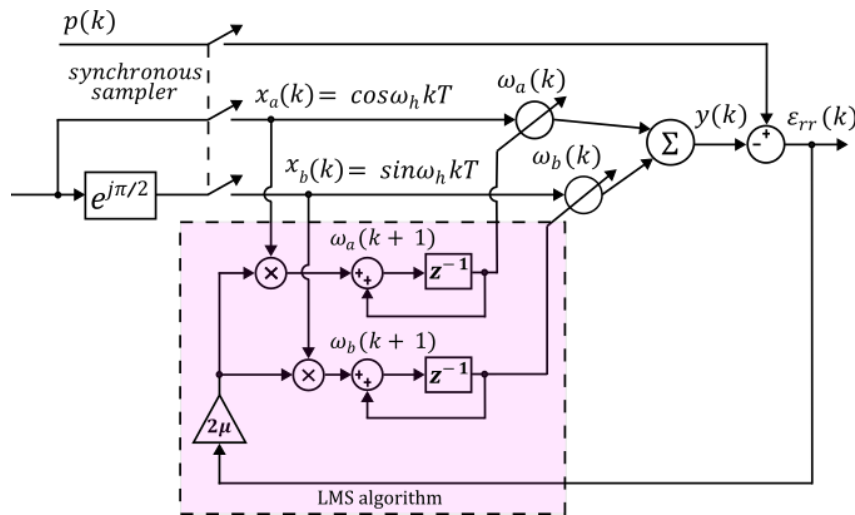


Fig. 3-3. Framework of the ASHA scheme.

The reference signals $x_a(k)$ and $x_b(k)$ are sinusoidal references where k represents the time index and T is the sampling period. Within $x_a(k)$ and $x_b(k)$, the frequency $\omega_h = 2\pi f_h$ is the selected harmonic, which should be eliminated from the primary input signal $p(k)$, with $\varepsilon_{rr}(k)$ representing the error estimate and $y(k)$, the output signal. The error estimate relates to the input signal and the output signal as follows:

$$\varepsilon_{rr}(k) = p(k) - y(k) \quad (3-7)$$

$$= p(k) - \mathbf{X}^T(k) \boldsymbol{\omega}(k)$$

where $\mathbf{X}(k)$ is the reference vector and $\boldsymbol{\omega}(k)$ is the weight vector and they are ultimately defined as

$$\begin{aligned} \mathbf{X}^T(k) &= [x_a(k) \ x_b(k)] = [\cos \omega_h kT \ \sin \omega_h kT] \\ \boldsymbol{\omega}^T(k) &= [\omega_a(k) \ \omega_b(k)] \end{aligned} \quad (3-8)$$

The product of reference vector $\mathbf{X}^T(k)$ and $\boldsymbol{\omega}^T(k)$ can be used to match the amplitude and phase of the sinusoidal interference in the primary signal. If $\varepsilon_{rr}^2(k)$ is used as an estimate of the mean square error (ξ) then $\xi = E[\varepsilon_{rr}^2(k)]$, which implies in each iteration step, the gradient $\hat{\nabla}(k)$ can be estimated as

$$\hat{\nabla}(k) = \begin{bmatrix} \frac{\delta \varepsilon_{rr}^2(k)}{\delta \omega_a(k)} \\ \frac{\delta \varepsilon_{rr}^2(k)}{\delta \omega_b(k)} \end{bmatrix} = 2\varepsilon(k) \begin{bmatrix} \frac{\delta \varepsilon_{rr}(k)}{\delta \omega_a(k)} \\ \frac{\delta \varepsilon_{rr}(k)}{\delta \omega_b(k)} \end{bmatrix} = -2\varepsilon_{rr}(k) \mathbf{X}(k) \quad (3-9)$$

Through (3-8) the weights can be adjusted iteratively in the direction of the gradient via the steepest descent algorithm to obtain the adaptive update of weights, ultimately expressed as [145]

$$\begin{aligned} \omega(k+1) &= \omega(k) - \mu \hat{\nabla}(k) \\ &= \omega(k) + 2\mu \cdot \mathbf{X}(k) \cdot \varepsilon_{rr}(k) \end{aligned} \quad (3-10)$$

where μ is the adaptation gain constant, which regulates the stability and the rate of convergence. Although larger values for μ generally tend to increase the convergence speed, they can also trigger instability. Alternatively, if μ is small the convergence speed will slow, resulting in unsatisfactory performance, consequently this parameter needs to be chosen appropriately.

Without averaging, by using $\varepsilon_{rr}^2(k)$ as an estimate of $\xi = E[\varepsilon_{rr}^2(k)]$, the gradient estimate (3-9) contains a substantial level of harmonics which is attenuated by the adaptive process (3-10). To quantify the attenuation, (3-10) can be viewed as the discrete implementation of an integrator with the product $\varepsilon_{rr}(k) \cdot \mathbf{X}(k)$ as an input. Assuming the reference signals from (3-8) both have an amplitude C , with an initial phase angle of ϕ then

$$x_a(k) = C \cos(\omega_h kT + \phi) \quad (3-11)$$

$$x_b(k) = C \sin(\omega_h kT + \phi)$$

$$y(k) = \omega_a(k).x_a(k) + \omega_b(k).x_b(k) \quad (3-12)$$

$$\begin{aligned} \omega_a(k+1) &= \omega_a(k) + 2\mu\varepsilon_{rr}(k) x_a(k) \\ \omega_b(k+1) &= \omega_b(k) + 2\mu\varepsilon_{rr}(k) x_b(k) \end{aligned} \quad (3-13)$$

It is noteworthy that $y(k)$ can be an accurate estimation of the ω_h frequency component in the primary input signal $p(k)$ in both steady and transient states.

3.3.2 Utilization of the ASHA scheme for Compensation of the Transverse Axis current

In a typical SPMSM drive system, current control loops are implemented to regulate the motor's electromagnetic torque. Since the motor torque is directly proportional to the motor current, when there are inaccuracies in current measurement, the control system may not apply the correct current, leading to fluctuations in the torque generated by the motor. These torque variations translate to speed fluctuations, as the motor speed is directly affected by the applied torque. Additionally, since the motor control architecture of the inner and outer loops are linked through a nested loop structure, errors in the current loop do propagate into the outer/speed loop, causing oscillations. The speed controller attempts to compensate for speed variations, but if current measurements fluctuate due to errors, the controller's attempt to stabilize the speed inadvertently causes oscillations in motor speed.

A key goal of this chapter is to suppress the speed ripple caused by hybrid errors and the ASHA algorithm is appropriately utilized for this suppression. In utilizing the ASHA scheme, the motor plant should be considered. Firstly, it is assumed that the algorithm neither changes the transfer function of the plant and associated control nor causes any interference with the dynamics of the system since its adaptation process is slow. The second assumption is that the harmonic content that needs to be eliminated by the strategy has a frequency value that lies beyond the bandwidth of regular control.

These assumptions pave the way for both the ASHA strategy and plant control to be analyzed separately since there are no interactions between regular control and the ASHA scheme. Hence

to integrate the strategy with the existing control of the motor plant, the output $y(k)$ of the scheme is multiplied by the inverse transfer function, $L_p^{-1}(z)$ of the motor plant. In detail, the input $p(k)$ is the speed tracking error, the selected frequency ω_h is the stator electrical frequency corresponding to the speed reference, and the q-axis compensation current represents the output. The combined architecture (consisting of the motor speed control system model and the ASHA scheme with $L_p^{-1}(z)$) is depicted in Fig. 3-4. In the depiction, $\bar{\omega}$ is the speed error without the influence of hybrid errors, ε_ω is the speed error after the influence of the q-axis hybrid error contribution, Δi_q (including the speed harmonics $\Delta\omega$ and $\bar{\omega}$), whereas $\tilde{\omega}$ represents the compensated speed corresponding to i_{q_ASHA} , and $\hat{\omega}$ denotes the speed error after the compensation process. It is expected that the speed harmonics $\Delta\omega$ in ε_ω can be suppressed by the compensation speed, $\tilde{\omega}$.

The electromagnetic torque for the SPMSM can be simplified as follows:

$$\begin{aligned} T_e &= 1.5p(\psi_{PM}i_q + (L_d - L_q)i_d i_q) \\ &= 1.5p\psi_{PM}i_q = m_K i_q \end{aligned} \quad (3-14)$$

Considering the relation that exists between the rotational inertia J , the electrical and load torques (T_e and T_L) as well as the q-axis current and speed, a transfer function for the motor plant can be generated as follows:

$$\begin{aligned} L_p(s) &= \frac{m_K}{Js} \\ L_p^{-1}(z) &= L_p^{-1}(s)|_{s=\frac{2z-1}{Tz+1}} = L_p^{-1}\left(\frac{2z-1}{Tz+1}\right) \end{aligned} \quad (3-15)$$

Besides, $U(z)$ represents the transfer function which determines the dynamic response from the current quantities to the speed quantities within the d-q frame. An expression for $U(z)$ can be derived as follows

$$\begin{aligned} U(s) &= \frac{\Delta\omega(s)}{\Delta i_q(s)} = \frac{\tilde{\omega}(s)}{i_{q_ASHA}(s)} = \frac{m_K s}{Js^2 + m_K k_p s + m_K k_i} \\ U(z) &= U(s)|_{s=\frac{2z-1}{Tz+1}} = U\left(\frac{2z-1}{Tz+1}\right) \end{aligned} \quad (3-16)$$

It can be deduced from Fig. 3-4 that through the speed error, the applied ASHA algorithm outputs the q-axis current compensation for the motor hybrid errors.

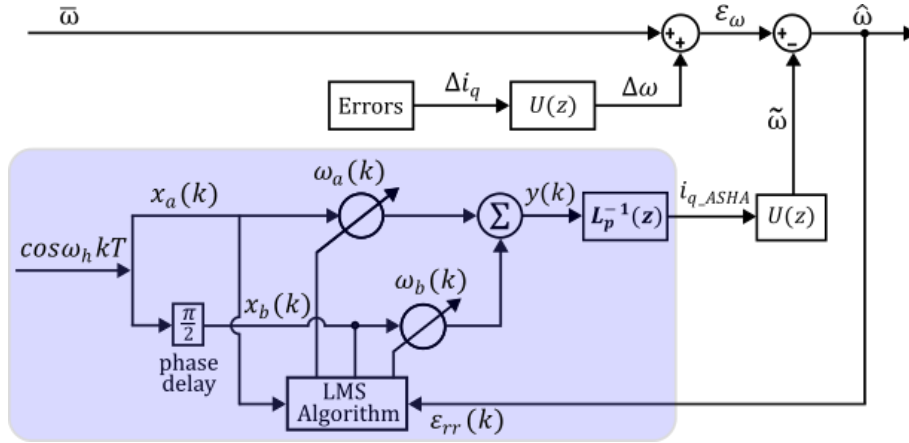


Fig. 3-4. Adoption of the ASHA algorithm into the motor control structure for compensation of hybrid errors.

Assuming that the slowly changing weights $\omega_a(k)$ and $\omega_b(k)$ are constant, the q-axis current compensation at the k^{th} instant is provided by

$$\begin{aligned} i_{q_ASHA} &= L_p^{-1}(s) y(k) \\ &= L_p^{-1}(s) (\mathbf{X}^T(k) \boldsymbol{\omega}(k)) \\ &= L_p^{-1}(s) (\omega_a(k) x_a(k) + \omega_b(k) x_b(k)) \end{aligned} \quad (3-17)$$

Combining (3-8), (3-15), (3-17) an expression could be obtained for the q-axis compensation current as

$$\begin{aligned} i_{q_ASHA} &= \frac{J}{m_K} s(\omega_a(k) \cos\omega_h kT + \omega_b(k) \sin\omega_h kT) \\ &= \omega_h \frac{J}{m_K} (-\omega_a(k) \sin\omega_h kT + \omega_b(k) \cos\omega_h kT) \end{aligned} \quad (3-18)$$

The output of the LMS algorithm is the weight vector $(\boldsymbol{\omega}^*)^T = [\omega_a^*(k) \ \omega_b^*(k)]$ combined with the other constant terms, hence (3-18) can be simplified as

$$i_{q_ASHA} = (\omega_b^*(k) \cos\omega_h kT - \omega_a^*(k) \sin\omega_h kT) \quad (3-19)$$

where

$$\begin{cases} \omega_a^*(k) = \omega_h \frac{J}{m_K} \omega_a(k) \\ \omega_b^*(k) = \omega_h \frac{J}{m_K} \omega_b(k) \end{cases}$$

Integrating the motor speed control system with the ASHA algorithm satisfactorily diminishes the q-axis current harmonics and reduces the speed ripple, nevertheless, the d-axis current harmonics remain untouched. Hence to make the suppression comprehensive in its effect, the ASHA scheme is enhanced.

3.3.3 Limitations of LMS-Based Adaptive of Filters

Despite its widespread adoption and practical advantages, the LMS algorithm exhibits several inherent limitations that can affect its performance in PMSM-based EV powertrains. These limitations become particularly significant in high-performance applications where fast dynamics, nonlinearities, and stringent real-time constraints are present.

One of the primary limitations of the LMS algorithm is its relatively slow convergence rate compared to more advanced adaptive filtering techniques such as RLS or Kalman filter-based estimators. The convergence speed of LMS is strongly dependent on the choice of step size, which must be carefully selected to ensure stability. A small step size results in slow adaptation and delayed error correction, which is undesirable in EV applications where rapid response to changing operating conditions is required. Conversely, a larger step size can accelerate convergence but may lead to instability or oscillatory behaviour, particularly in noisy environments. This inherent trade-off between convergence speed and stability limits the responsiveness of LMS in dynamic driving conditions [250].

Another significant limitation lies in the steady-state error performance of the LMS algorithm. Even after convergence, LMS typically exhibits a residual error, often referred to as misadjustment, due to its stochastic gradient descent nature [251]. In PMSM drives, this can manifest as persistent current distortion or torque ripple, which may degrade efficiency and affect ride quality. In contrast, algorithms such as RLS or adaptive Kalman filters are capable of achieving lower steady-state error due to their more accurate parameter estimation mechanisms [252].

The performance of LMS is also sensitive to the statistical properties of the input signals, particularly their correlation. In systems where the input signals are highly correlated, such as in electric drives with coupled d–q axis dynamics, the convergence of LMS can be significantly slowed. This phenomenon, often associated with eigenvalue spread in the input signal

covariance matrix, reduces the effectiveness of LMS in complex, multivariable control environments typical of PMSM powertrains [253].

Another important limitation is the algorithm's sensitivity to measurement noise and disturbances. Since LMS updates its filter coefficients based on instantaneous error, noisy measurements can introduce fluctuations in the adaptation process, resulting in increased steady-state variance and degraded filtering accuracy [254]. While this sensitivity can be mitigated through modifications such as normalised LMS (NLMS) or variable step-size approaches, it remains a fundamental challenge in noisy environments such as those encountered in EV power electronics.

Finally, although LMS is computationally efficient, its performance scalability is limited when extended to more complex system architectures, such as multi-motor EV powertrains. In such systems, interactions between multiple drive units introduce coupled dynamics and distributed error sources that are not easily handled by conventional LMS structures. This limitation necessitates the development of more advanced or coordinated filtering strategies when dealing with multi-motor configurations.

3.3.4 Enhancement of the ASHA scheme for Compensation of the d-axis current

By considering the contribution of the first-order harmonics to the periodic ripples, the dq-axis harmonics can be expressed as [2]

$$\begin{cases} \Delta i_d = I_1 \sin(\theta_e + \varphi_1) \\ \Delta i_q = I_1 \cos(\theta_e + \varphi_1) \end{cases} \quad (3-20)$$

where θ_e represents the electrical angle, $\theta_e = \omega_e t = 2\pi f_e t$, I_1 represents the amplitude of the stator current and φ_1 represents the argument of the function. By honing in on the fundamental frequency for an instance where, $\omega_h = \omega_e$, the dq-axis harmonics (as a result of the hybrid errors) represented in (3-20) can be expanded via classical trigonometric identities as

$$\begin{cases} \Delta i_d = I_1 \sin(\omega_h kT + \varphi_1) \\ \quad = I_1 \sin \varphi_1 \cos \omega_h kT + I_1 \cos \varphi_1 \sin \omega_h kT \\ \Delta i_q = I_1 \cos(\omega_h kT + \varphi_1) \\ \quad = I_1 \cos \varphi_1 \cos \omega_h kT - I_1 \sin \varphi_1 \sin \omega_h kT \end{cases} \quad (3-21)$$

By combining (3-19) and (3-21), the corresponding relationship between the weights can be

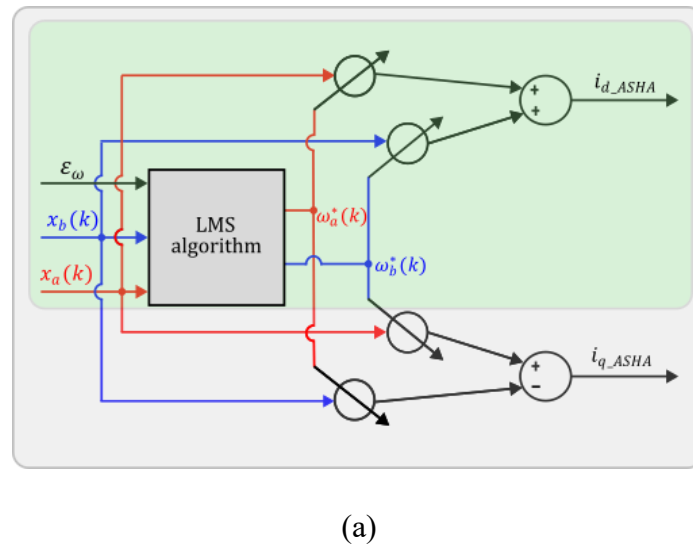
established as follows:

$$\begin{cases} I_1 \sin \varphi_1 = \omega_a^*(k) \\ I_1 \cos \varphi_1 = \omega_b^*(k) \end{cases} \quad (3-22)$$

Consequently, the compensation for the d-axis current harmonics is obtained as

$$i_{d_ASHA} = \omega_a^*(k) \cos \omega_h kT + \omega_b^*(k) \sin \omega_h kT \quad (3-23)$$

As such by utilizing (3-10), (3-19) and (3-23), the proposed strategy concurrently compensates for the dq-axis harmonics (originating from the hybrid errors). Fig. 3-5 illustrates the E-ASHA scheme proposed to resolve the hybrid error problem, and how it is ultimately integrated within the FCS-MPCC. The inputs include the speed error ε_ω and the reference vector $\mathbf{X}(k)$, whereas the outputs are the dq-axis current compensation i_{d_ASHA} and i_{q_ASHA} . As evidenced within the figure, the proposed strategy does not tamper with the conventional control structure. In the proposed scheme, a key parameter is the step size μ of the LMS algorithm, which is related to the stability of the system and the speed of convergence. Concerning system stability, μ does not permit arbitrary settings and needs to be chosen appropriately (neither too small nor too large).



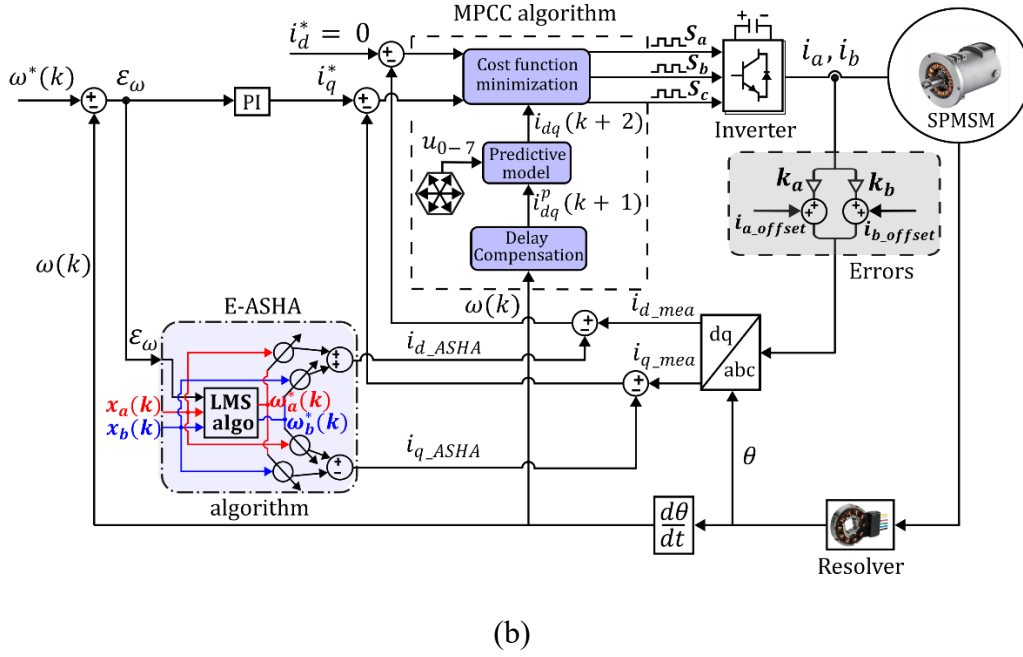


Fig. 3-5. E-ASHA algorithm. (a) Block diagram. (b) Integration of strategy within the MPCC-SPMSM Drive System.

The computational burden of the E-ASHA can be understood as an extension of classical LMS-based adaptive filtering, with additional operations introduced to enhance convergence, harmonic suppression, and delay compensation. A standard LMS filter with length N requires $2N + 1$ multiplications and $2N$ additions per sampling instant. It avoids the divisions and square roots common in other observers. In contrast, RLS-based algorithms involve matrix operations and heavy divisions, while EKFs require complex matrix inversions and covariance updates, often exceeding the computational capacity of standard automotive microcontrollers, leading to complexity on the order of $O(N^2)$ to $O(N^3)$, depending on system size [255]. This often renders such advanced estimation techniques impractical for high-frequency control loops in EV applications. As such, in comparison with other cutting-edge estimation strategies, E-ASHA offers a significantly lower computational cost while providing enhanced error mitigation performance, making it well-suited for real-time implementation in PMSM-based EV powertrains. Additionally, while it slightly reduces convergence speed compared to the other state-of-the-art approaches, it offers the best efficiency-to-performance ratio by keeping the processor load low while effectively suppressing torque ripple.

3.4 Experimental Verification

The proposed strategy is applied to a three-phase 1KW SPMSM drive system to test its feasibility and validity. The experimental platform is depicted in Fig. 3-6.

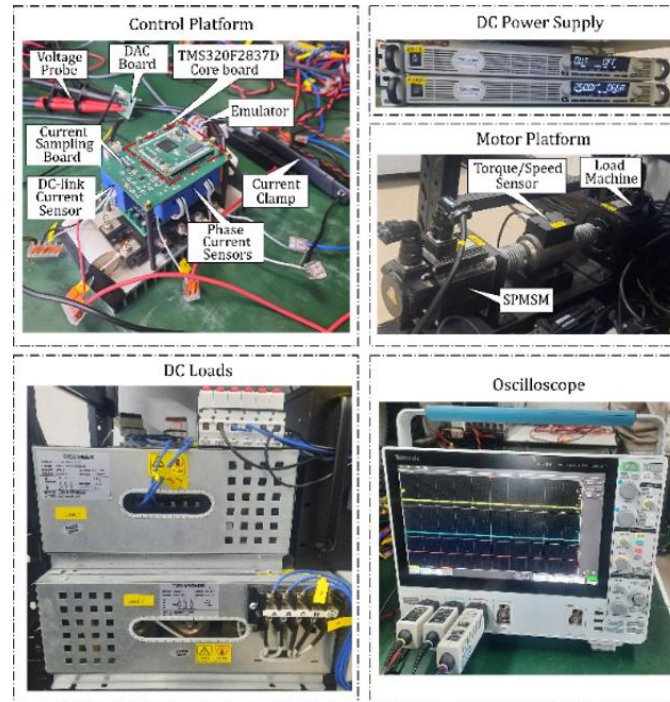


Fig. 3-6. Experimental Setup depicting the Control Platform, DC Power Supply, DC Loads and Oscilloscope.

The key parameters of the SPMSM are shown in Table 3-2.

TABLE 3-2 Main Parameters of SPMSM

Parameter	Value	Parameter	Value
Rated power	1.0kw	Line inductance	2.64mH
Rated current	4A	Line resistance	1.05 Ω
Rated speed	2000rpm	Pole pairs	4
Rated torque	5N.m	Adaptation constant (μ)	5e-06
Rated voltage	220V	Moment of Inertia (J)	1.06e-3 Kg.m ²

A DC power supply (TDK G300-11.5-1P208-M) provides 200V for the power boards and inverters. The inverter is an integrated power module, Mitsubishi PM75RLA120, with a

switching frequency of 10KHz. The current sensors used in the drive are isolated hall-effect current sensors (LA25-P). The control unit is a DSP TMS320F2879D. The load machine is connected with a resistor box. All the current values are redetected by current clamps (Tektronix TCP0030A) for signal sampling and an oscilloscope (Tektronix MOS46) is utilized for recording. Within the TMS320F2879D processor, the prediction model is modified to account for the analog and digital delays and a control action is applied based on the predicted state, rather than the current sampled state. The current sampling errors are also introduced to the system via software to verify the method accurately. Offset and scaling errors are directly introduced into the current signal converted from the ADC port. The parameters of the artificially introduced current sampling errors are given in Table 3-3.

TABLE 3-3 Parameters of Current Measurement Errors

Parameter	Value	Parameter	Value
f_A	-0.25	k_A	0.90
f_B	0.50	k_B	1.05

3.4.1 Steady-State Performance Comparative Validation

When the motor runs at 300 and 1800 rpm, respectively, under light and heavy load conditions, the errors shown in Table 3-3 are artificially introduced. The changes in the three-phase and dq-axis currents together with the harmonic analysis for the distinct loads after the introduction of the errors are depicted in Fig. 3-7. The significant increase of the harmonic component within the dq-axis currents at the two speeds after the introduction of the errors leads to fluctuations in the output speed and torque ripples will emerge on the motor shaft, which will, in turn, degrade the system's performance. Consequently, these errors will have to be compensated for to eliminate their detrimental impact.

Having analyzed the extent of the impact of the errors under the two different scenarios, the compensation algorithm is applied to both loads at the respective speeds. The changes that ensue in the currents (both three-phase and dq-axis) are captured together with the harmonic profile, in Fig. 3-8. At low speed, the proposed E-ASHA effectively compensates for hybrid errors for both load conditions, demonstrating load-independent harmonic learning. At 1800 rpm, inverter non-idealities, control delays and parameter mismatch amplify harmonic content,

while dq-axis coupling becomes more pronounced. Although suppression effectiveness decreases under heavy load at high speed, the algorithm still maintains more than 46% reduction in i_q , preventing uncontrolled torque oscillations. Quantitatively, the reduction in speed ripple can be approximated as $\Delta\omega \approx 1/J \int \Delta T_e dt$, thus even a 46-54% reduction in torque ripple at high speed yields a disproportionately larger improvement in speed smoothness due to reduced excitation of mechanical resonance modes. The tables corresponding to the percentage error suppression for the two loads are depicted in Table 3-4.

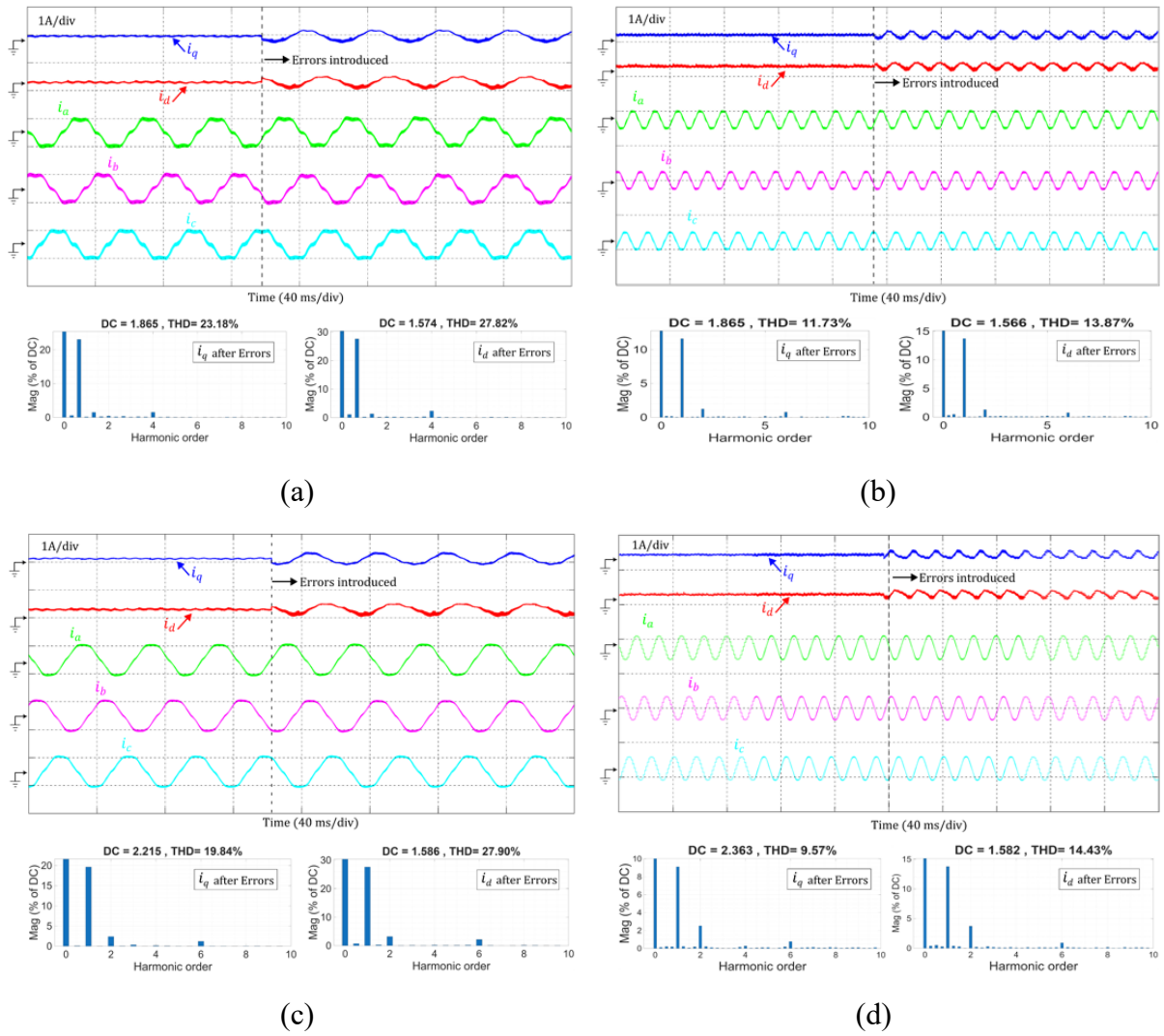


Fig. 3-7. Comparative analysis of three-phase and dq-axis currents after the introduction of hybrid errors. (a) Light load-300 rpm. (b) Light load-1800 rpm. (c) Heavy load-300 rpm. (d) Heavy load-1800 rpm.

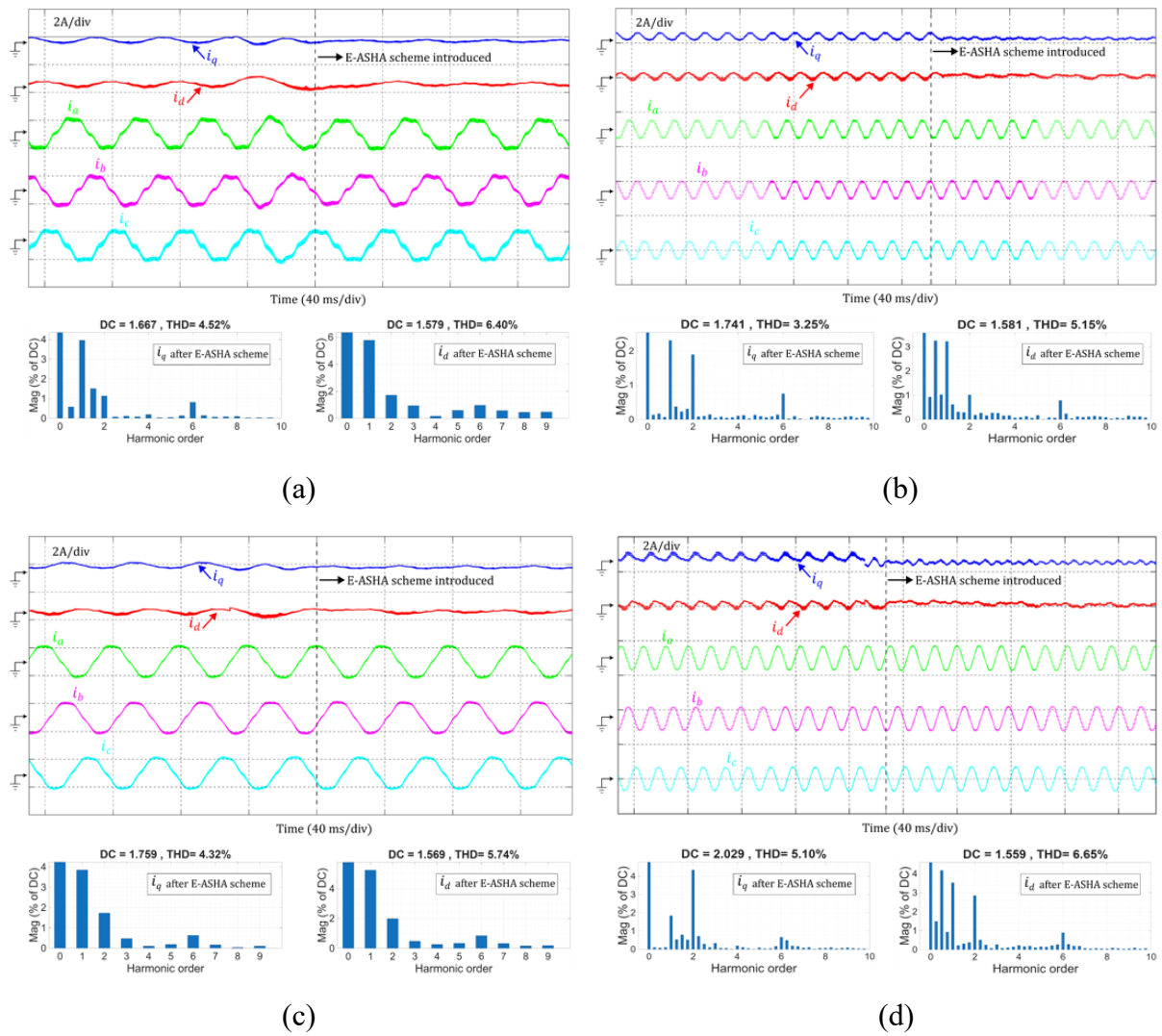


Fig. 3-8. Corrective effect of E-ASHA algorithm at distinct motor speeds. (a) Light load-300 rpm. (b) Light load-1800 rpm. (c) Heavy load-300 rpm. (d) Heavy load-1800 rpm.

TABLE 3-4 Hybrid Error-Suppression Capability of The Proposed E-ASHA

Load	Speed	THD After Error	THD After E-ASHA	Suppression (%)
Light Load	300 rpm	$i_q = 23.18$	$i_q = 4.52$	80.50
		$i_d = 27.82$	$i_d = 6.40$	77.00
Light Load	1800 rpm	$i_q = 11.73$	$i_q = 3.25$	72.29
		$i_d = 13.87$	$i_d = 5.15$	62.87
Heavy Load	300 rpm	$i_q = 19.84$	$i_q = 4.32$	78.23
		$i_d = 27.90$	$i_d = 5.74$	79.43

Heavy Load	1800 rpm	$i_q = 9.57$	$i_q = 5.10$	46.71
		$i_d = 14.43$	$i_d = 6.65$	53.92

3.4.2 Comparative Verification under Speed change

The experimental results for a step-speed change with respect to a medium load are depicted in Fig. 3-9 (a) and (b). As shown in the figures, the dq-axis current harmonics are significantly eliminated after the application of the compensation scheme. When the motor speed changes suddenly, the adaptive filter may struggle to track the rapid change immediately. This lag causes temporary discrepancies between the filter's output and the actual signal leading to slight oscillations (as depicted in Fig. 3-9 (b)). In other words, with an abrupt speed change, the adaptive filter can exhibit slight tracking lag or oscillations due to the delay in the filter's adaptation, where the filter coefficients do not update quickly enough to accommodate the new operating conditions.

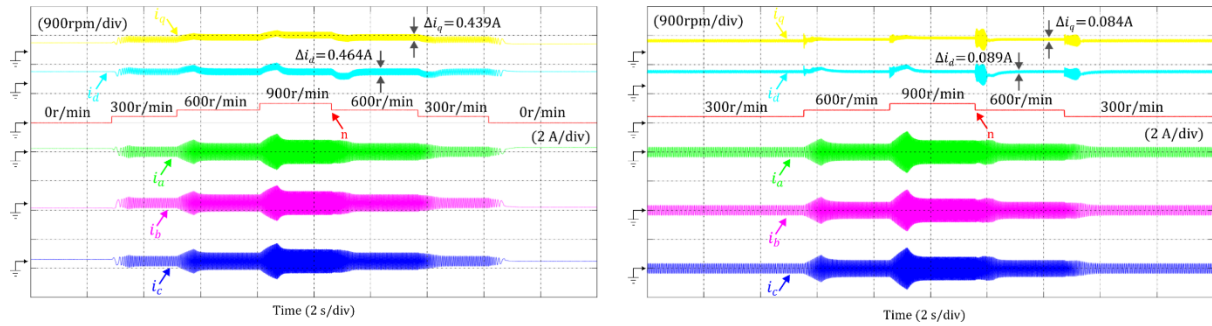


Fig. 3-9. Transient analysis for medium load at step-speed conditions. (a) With hybrid errors introduced. (b) After the application of the E-ASHA algorithm.

3.4.3 Comparative Validation under Load Torque change

The experimental result under step load torque with the motor running at 900 rpm is shown in Fig. 3-10. As depicted by the figure, the dq-axis current fluctuations corresponding to the different loads are significantly eradicated once the compensation algorithm is implemented. Finally, how the proposed method performs relative to other error compensation schemes is shown in Table 3-5.

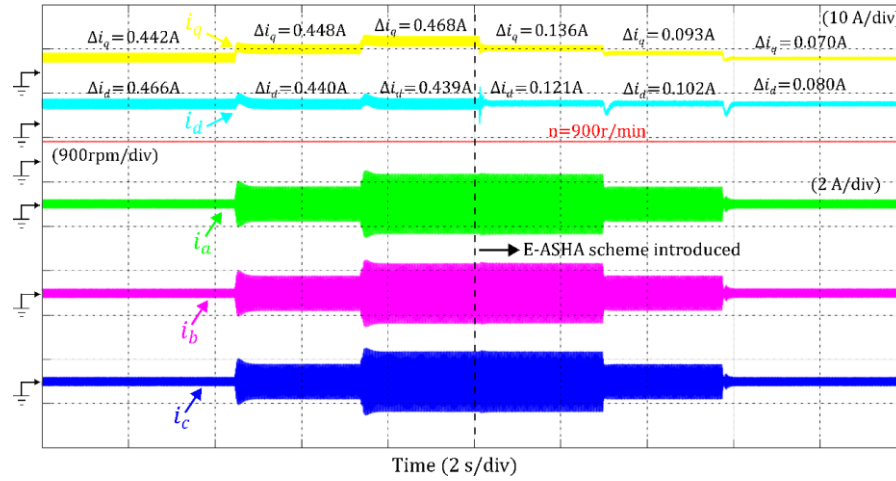


Fig. 3-10. Experimental analysis under step load torque conditions.

TABLE 3-5 Comparison of some Modern CME Compensation Schemes with the Proposed Strategy

Feature	[256]	[257]	[258]	Proposed e-ASHA-FCS-MPCC
Control strategy	PI + ESO (Speed loop)	PI current control	PI current control	FCS-MPCC (10 kHz)
CME Source Used	Speed ripple	dq-current ripple	dq-current harmonics	dq-current harmonics (predictive)
Harmonics Targeted	1 st , 2 nd (fixed)	1 st , 2 nd	1 st , 2 nd (multi-harmonic)	Selective (adaptive)
Adaptivity to Speed & Load	Moderate	Moderate	High	Very High
Predictive Capability	×	×	×	✓
Online CME Compensation	✓	✓	✓	✓
Computational Cost	Low	Low	Medium-High	Medium (bounded FCS)

Table 3-5 shows that unlike existing adaptive harmonic suppression methods such as

ADALINE, which rely on reactive compensation and are limited by control loop bandwidth and delay-induced instability, the proposed E-ASHA-FACS-MPCC framework achieves unified predictive and multi-harmonic suppression of hybrid errors directly within the control loop, enabling superior ripple attenuation and robustness across wide operating conditions.

3.4.4 Scalability of EV Traction Systems

Although the experimental validation of the proposed E-ASHA-FCS-MPCC strategy is conducted on a 1 kW SPMSM platform, the applicability of the method to high-power EV traction systems can be justified from both theoretical and practical perspectives.

From a modelling standpoint, the proposed control strategy operates on the basis of normalized machine equations in the synchronous reference frame. The underlying mechanisms responsible for torque and speed ripple namely CMEs, inverter nonlinearity, and delay-induced phase distortion, are inherently scale-invariant phenomena. Consequently, the harmonic distortion characteristics in the dq-axis currents and their impact on electromagnetic torque persist across different power levels. As such, the effectiveness of the E-ASHA algorithm in suppressing these harmonics is expected to translate to higher-power systems, including EV traction drives.

Nevertheless, several practical factors distinguish low-power laboratory prototypes from high-power EV implementations. First, EV traction inverters typically operate at lower switching frequencies due to semiconductor thermal constraints, which may influence the prediction horizon and switching optimization in FCS-MPCC. Second, the electrical parameters of high-power machines (e.g., stator inductance and resistance) result in different electrical time constants, requiring appropriate retuning of controller gains and adaptive parameters. Third, the mechanical inertia in EV drivetrains is significantly higher, which naturally attenuates speed ripple; therefore, the primary benefit of the proposed method in such applications is expected to manifest as torque ripple reduction and improved acoustic noise performance rather than pronounced speed ripple suppression.

In addition, the computational burden of the proposed method must be considered in the context of automotive-grade embedded platforms. While the E-ASHA algorithm introduces additional adaptive harmonic processing, its integration within the finite control set framework avoids the

need for external observers or cascaded compensation loops, thereby maintaining a bounded and predictable computational complexity suitable for real-time implementation.

Overall, while quantitative performance metrics may vary due to hardware and operating constraints, the proposed E-ASHA–FCS-MPCC strategy remains fundamentally applicable to EV traction systems. Its ability to simultaneously address current measurement errors and delay-induced distortions in a predictive and unified manner provides a strong foundation for improving torque quality and robustness in high-power electric drives.

In addition to scaling considerations, parameter uncertainty plays a more significant role in high-power EV traction systems than in low-power laboratory prototypes. Variations in stator resistance due to temperature, magnetic saturation effects on inductance, and inverter non-idealities introduce model mismatch that can degrade the prediction accuracy of FCS-MPCC. While the 1 kW experimental setup exhibits relatively stable parameters, EV systems are subject to wider and more dynamic parameter variations. Nevertheless, the proposed E-ASHA algorithm mitigates this limitation by relying on real-time current signal adaptation rather than purely model-based compensation. As a result, the method retains robustness against parameter uncertainty and is expected to maintain effective ripple suppression performance even under the harsher operating conditions of EV applications, albeit with some performance degradation compared to ideal laboratory conditions.

3.5 Summary

Hybrid errors within the SPMSM drive result in degraded dynamic performance, reduced stability margins, and increased torque ripple. While the conventional Adaptive Selective Harmonic Annulation (ASHA) algorithm effectively mitigates q-axis harmonic components, its inability to compensate d-axis harmonics limits its overall performance and results in residual speed oscillations. To overcome this limitation, an Enhanced Adaptive Selective Harmonic Annulation (E-ASHA) algorithm was developed. The proposed method extends the capability of the original ASHA framework by enabling simultaneous compensation of both d-axis and q-axis harmonic components. This comprehensive harmonic suppression significantly improves the dynamic performance of the system and effectively eliminates undesirable speed ripple. The efficacy of the proposed strategy was verified through experiments. The proposed scheme has the following advantages:

- 1) It achieves up to 80.5% current ripple suppression and an estimated 80% torque ripple attenuation at low speed, while maintaining greater than 46% torque ripple suppression at high speed under heavy load scenarios. By integrating LMS-based adaptive harmonic learning within an FCS-MPCC framework, the method compensates for hybrid errors across wide speed and load ranges with moderate computational cost.
- 2) Its adaptability, computational efficiency, and selectivity make it a unique and effective approach compared to other compensation methods. While other strategies may offer specific advantages, the partnership of E-ASHA with the LMS algorithm strikes an optimal balance between performance and practicality, making it well-suited for real-time applications in power electronics and motor control systems.

Chapter 4 Correlative Correction of CMEs for Quad-Motor Electric Drivetrains

CMEs pose a significant challenge in quad-motor drive (QMD) systems for electric vehicles, where small inaccuracies from individual subsystems accumulate and interact at the system level, leading to torque oscillations, speed ripples, and degraded coordination among motors. Unlike conventional approaches that treat each motor independently, this chapter presents a novel correlative correction strategy that leverages the inherent coupling between multiple motor subsystems through a shared DC-link. The proposed method exploits the physical relationship between inverter switching states and current flow paths to establish an overdetermined system of equations, enabling simultaneous estimation and compensation of offset and scaling errors across all four motor drives without requiring detailed motor models or complex observers. The correction mechanism operates in a coordinated manner, enforcing consistency among subsystems while maintaining distributed local control implementation.

The effectiveness of the proposed method is evaluated through a comprehensive simulation framework that assesses CME estimation performance under controlled EMI disturbances across multiple operating scenarios. These studies examine the robustness and accuracy of the estimation process under varying noise conditions. Furthermore, experimental validation is conducted in both EMI and non-EMI environments to verify the practical applicability of the approach. The results demonstrate consistent and reliable CME estimation performance, confirming the robustness of the proposed method under realistic operating conditions.

Overall, the proposed strategy provides a scalable and computationally efficient solution for system-level CME compensation in multi-motor electric drivetrains, addressing a critical limitation of conventional single-drive-based approaches.

4.1 Introduction

QMD systems are emerging as a key architecture in advanced electric vehicle (EV) platforms due to their ability to provide independent torque control at each wheel, enabling enhanced traction, stability, and dynamic performance [259], [260], [261]. By distributing propulsion across four electric machines, QMDs offer improved fault tolerance and flexibility compared

to conventional single- or dual-motor drivetrains. However, this architectural advantage introduces increased system complexity, particularly in sensing, control coordination, and real-time current regulation. Unlike single-motor drives, where control inaccuracies remain localized, quad-motor architectures introduce a fundamentally different challenge in the sense that small errors originating from individual subsystems accumulate and interact at the system level.

Accurate current measurement is fundamental to high-performance motor control strategies such as field-oriented control (FOC), where torque production is directly governed by the q-axis current component. In QMD systems, each motor relies on local current sensing for feedback control, making the overall system highly sensitive to measurement inaccuracies. These inaccuracies, commonly referred to as current measurement errors (CMEs), arise from multiple sources including sensor offset, gain mismatch, analog-to-digital conversion errors, inverter non-idealities, and electromagnetic interference (EMI). In motor drive systems, CMEs are primarily classified as offset and scaling errors. Offset errors generate torque oscillations at the fundamental electrical frequency, while scaling errors induce second-order harmonic torque components [262].

In the case of CMEs within QMDs, their existence in each motor subsystem can propagate through the inner current control loops and collectively manifest as amplified torque and speed ripples. As all four motors contribute simultaneously to vehicle propulsion, asynchronous or nonuniform current errors can disrupt torque sharing and degrade overall system performance.

Fig. 4-1 depicts the QMD for high-performance EVs, highlighting how the electric axle drive (e-axle) integrates the motor, power electronics and transmission into a single, highly efficient, compact unit that directly drives the vehicle's axle, saving both space and cost. Each motor operates independently, allowing precise control over power and torque distribution. The system achieves symmetry and optimized performance using torque vectoring, real-time feedback loops, and intelligent control algorithms. The only linkage between the four motors is in software via a central control unit. Within the figure, CSU signifies the current sampling unit, and EFB denotes electrical feedback.

While CMEs are well studied in single-motor drive systems, their impact is significantly amplified in QMD configurations. In contrast to single-drive systems, where errors primarily degrade local performance, CMEs in QMDs lead to inter-motor inconsistencies such as unequal torque sharing, circulating currents, and degraded coordination among motor subsystems.

These effects manifest as increased current ripple, torque oscillations, reduced efficiency, and compromised dynamic response. Furthermore, the presence of EMI in automotive environments exacerbates these issues by introducing additional noise and harmonic distortion into current measurements.

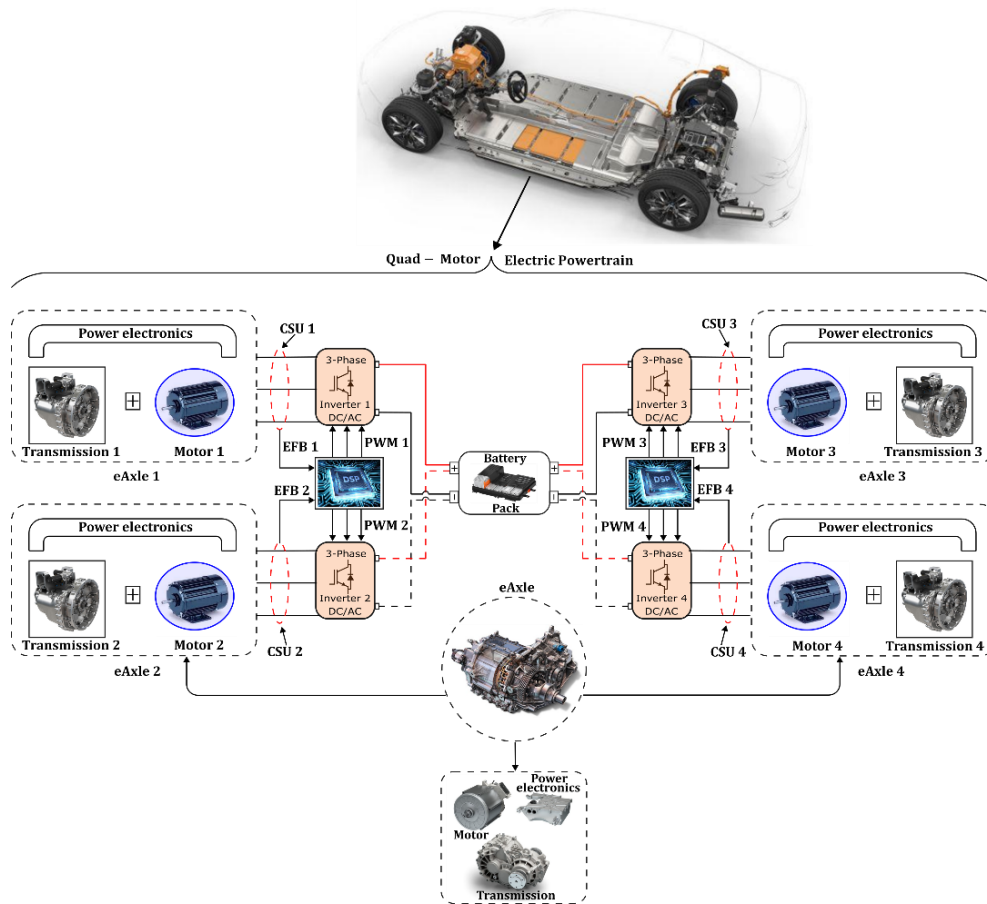


Fig. 4-1. Contemporary architecture of QMD for high-performance electric cars and utility vehicles.

In single-motor PMSM systems, extensive research has focused on CME mitigation and fault-tolerant current sensing. Observer-based approaches are among the most widely adopted techniques. For example, sliding-mode observer (SMO)-based methods have been proposed to estimate and compensate current sensor faults by treating them as lumped disturbances, thereby improving robustness under parameter uncertainties [263]. More recently, adaptive and fixed-time observer frameworks have been developed to enable fast and simultaneous estimation of multiple faults in PMSM drives [264]. In addition, disturbance observer (DOB)-based control strategies have been integrated with model predictive control (MPC) to enhance disturbance

rejection and compensate for measurement inaccuracies in real time [265]. Model-based and predictive control approaches have also gained significant attention. Recent work in literature has demonstrated that motor-parameter-free model predictive current control can improve robustness against parameter mismatch and measurement uncertainties [266]. Similarly, predictive current error compensation strategies have been introduced to explicitly account for current deviations within the control loop, leading to improved steady-state and transient performance [267]. These approaches highlight the importance of incorporating error compensation mechanisms directly into the control framework.

Another important line of research focuses on analytical modelling and reconstruction of current measurement errors. For instance, current signature modelling techniques have been proposed to characterize the impact of sensor faults on PMSM current waveforms, enabling systematic analysis and compensation of offset and gain errors [268]. Furthermore, single-shunt and DC-link current reconstruction methods have been investigated to reduce sensor count while maintaining acceptable accuracy, particularly in cost-sensitive applications [269]. While effective, these methods often rely on precise timing, switching conditions, or complex estimation algorithms.

In parallel, recent studies have explored advanced disturbance suppression and estimation techniques. Multi-sliding mode control and model reference adaptive systems (MRAS) have been proposed to suppress current disturbances and improve estimation accuracy under nonlinear and time-varying conditions [270]. Data-driven and learning-based approaches are also emerging, leveraging neural networks and adaptive estimation frameworks to enhance current prediction and compensate for uncertainties in PMSM drives.

Despite these advances, the majority of existing CME compensation techniques are developed for single-motor systems. In contrast, research on multi-motor drive systems has primarily focused on coordinated control, fault tolerance, and power-sharing strategies rather than measurement accuracy. In multi-drive configurations, especially those with a shared DC-link, interactions among parallel motor–inverter units introduce additional challenges such as circulating currents, coupling effects, and synchronization issues. These interactions amplify the impact of CMEs, as inconsistencies in current measurements across different subsystems can lead to unequal torque distribution and degraded system-level performance.

Recent works on multi-phase and multi-drive systems have highlighted the increased sensitivity of current control to modelling inaccuracies and cross-coupling effects [271].

However, these studies typically address control design rather than systematic error compensation. Moreover, existing CME mitigation methods generally treat each motor independently and do not exploit the inherent correlations between multiple subsystems operating on a shared power bus.

Furthermore, in automotive environments, EMI-induced disturbances often exhibit correlated behaviour across sensing channels, particularly in compact multi-inverter configurations. This further limits the effectiveness of independent calibration techniques and underscores the need for coordinated or system-level compensation strategies.

In summary, while significant progress has been made in CME mitigation for single-motor PMSM drives through observer-based, predictive, and model-based approaches, there remains a critical gap in extending these techniques to multi-motor systems such as QMD architectures. In particular, existing methods do not adequately address inter-motor coupling effects or leverage shared system variables, such as DC-link current, for unified error compensation. This gap motivates the development of correlative CME correction strategies tailored for multi-motor platforms, as proposed in this work.

The proposed CME correction method is inherently coordinated at the system level, rather than being independently applied to each motor drive. Although each motor–inverter subsystem performs local current measurement and control, all four drives are interconnected through a shared DC-link, which introduces intrinsic coupling among them. Unlike conventional approaches that treat each motor independently, the proposed method leverages the correlation between individual phase currents and the common DC-link current. This enables simultaneous estimation and compensation of CMEs across all motor subsystems. As a result, the correction process inherently enforces consistency among the four drives, reducing inter-motor discrepancies such as unequal torque sharing and circulating currents. Therefore, while the control implementation remains distributed (local controllers per motor), the CME correction mechanism operates in a coordinated manner, exploiting shared system variables to achieve system-wide accuracy improvement.

The main contributions of this work are summarized as follows:

1. A systematic analysis of CME propagation in QMD architectures, highlighting inter-motor coupling effects and limitations of conventional single-drive compensation methods.

2. A novel correlative correction strategy that utilizes DC-link and phase current relationships for multi-motor error estimation.
3. A scalable and low-complexity implementation suitable for real-time automotive applications.
4. Experimental validation demonstrating significant reduction in current ripple and improved transient performance under both nominal and EMI conditions.

The remainder of this chapter is organized as follows: Section II describes the QMD system architecture and modelling. Section III presents the details of the proposed correlative correction approach. Section IV provides information about areas where currents can be directly sampled for reconstruction. Section V deals with simulation results and discussion, while Section VI discusses experimental results. Finally, Section VII concludes the chapter.

4.2 Current Equations Corresponding to the QMD Architecture

The proposed method does not require a detailed model of the full vehicle powertrain, such as vehicle dynamics, drivetrain mechanics, or tire-road interaction. Instead, it relies primarily on the electrical dynamics of the motor drive system, including inverter switching behaviour, phase currents, and DC-link current relationships.

Specifically, the method utilizes measured phase currents from each motor drive, the shared DC-link current, and known switching states within a structured PWM framework.

By exploiting the physical relationship between inverter switching states and current flow paths, the proposed approach establishes analytical correlations that enable estimation of offset and gain errors without requiring mechanical or vehicle-level modelling.

This significantly reduces implementation complexity and enhances scalability, making the method suitable for real-time automotive applications where full powertrain models may be unavailable or computationally expensive.

The quad-motor drive (QMD) system consists of four motor–inverter units connected to a common DC-link. Although each inverter operates independently, the shared DC-link creates an electrical coupling between all subsystems that can be exploited for system-level analysis.

For each motor k ($k = 1, 2, 3, 4$), the phase voltage equations can be expressed as:

$$V_{A,k} = R_s \cdot i_{A,k} + L_s \cdot \frac{d}{dt} i_{A,k} + e_{A,k} \quad (4-1)$$

$$V_{B,k} = R_s \cdot i_{B,k} + L_s \cdot \frac{d}{dt} i_{B,k} + e_{B,k}$$

$$V_{C,k} = R_s \cdot i_{C,k} + L_s \cdot \frac{d}{dt} i_{C,k} + e_{C,k}$$

where R_s and L_s are the stator resistance and inductance and $e_{A,k}$, $e_{B,k}$ and $e_{C,k}$ are the back-EMFs and $i_{A,k}$, $i_{B,k}$ and $i_{C,k}$ are the stator currents.

Each inverter draws current from the shared DC-link depending on its switching state. For motor k, the DC-link current contribution is given by:

$$i_{DC,k} = S_{A,k} \cdot i_{A,k} + S_{B,k} \cdot i_{B,k} + S_{C,k} \cdot i_{C,k} \quad (4-2)$$

where $S_{A,k}$, $S_{B,k}$ and $S_{C,k}$ are the switching functions that can take values of 0 or 1 depending on the inverter state.

The total DC-link current is therefore the sum of all four motors:

$$\begin{aligned} i_{DC} = & (S_{A,1} \cdot i_{A,1} + S_{B,1} \cdot i_{B,1} + S_{C,1} \cdot i_{C,1}) + (S_{A,2} \cdot i_{A,2} + S_{B,2} \cdot i_{B,2} + S_{C,2} \cdot i_{C,2}) \\ & + (S_{A,3} \cdot i_{A,3} + S_{B,3} \cdot i_{B,3} + S_{C,3} \cdot i_{C,3}) + (S_{A,4} \cdot i_{A,4} + S_{B,4} \cdot i_{B,4} \\ & + S_{C,4} \cdot i_{C,4}) \end{aligned} \quad (4-3)$$

This equation forms a global constraint that links all phase currents through the shared DC-link.

In practice, the measured currents are not ideal and include gain and offset errors. For example, the measured phase-a current of motor k can be written as:

$$i_{A,k}(meas) = (1 + \alpha_{A,k}) \cdot i_{A,k} + \beta_{A,k} \quad (4-4)$$

where $\alpha_{A,k}$, $\beta_{A,k}$ and $i_{A,k}$ represent the gain/scaling error, the offset error and the true/actual phase-a current. Similar expressions apply to the other phases.

Substituting measured currents into the DC-link equation introduces a mismatch between the measured DC-link current and the reconstructed current from phase measurements.

$$i_{DC,meas} = \sum_{k=1}^4 (S_{A,k} \cdot i_{A,k}(meas) + S_{B,k} \cdot i_{B,k}(meas) + S_{C,k} \cdot i_{C,k}(meas)) \quad (4-5)$$

This inconsistency provides the basis for estimating current measurement errors (CMEs).

4.2.1 Essential Features of the QMD System

A QMD system is made up of four motor subsystems with each subsystem consisting of a distinct inverter and motor. As illustrated in Fig. 4-2, four inverters, realized by paralleled-inverter-fed topology are supplied by a single DC-bus voltage source V_{DC} , with positive (Q) and negative (R) output terminals. Two out of the three-phase cables of each motor subsystem establish connection with the output terminals of the corresponding inverter bridge arm and then pass through current sensor detection ports. The DC-link current sensor (i_{DC}) ultimately measures the sum of all four inverter input currents. In Fig. 4-2, i_{A1} , i_{B1} , i_{C1} , i_{A2} , i_{B2} , i_{C2} , i_{A3} , i_{B3} , i_{C3} and i_{A4} , i_{B4} , i_{C4} are the three-phase currents of motor subsystems 1, 2, 3, and 4 respectively. The output current of the single DC-bus voltage source is denoted by i_{DC} . These currents do not contain any measurement errors and are ideal in nature. Contrary to the actual/real currents, the measured currents contain CMEs (offset and scaling errors) with the offset errors indicated by f_{xn} (with $x = A, B$ and $n = 1$ to 4 for phase current sensors) and f_{DC} (for the DC-bus current sensor), whereas the scaling errors are denoted by k_{xn} (with $x = A, B$ and $n = 1$ to 4 for phase current sensors) and k_{DC} (for the DC-bus current sensor). The measured currents for all four motors are given in Table 4-1. In the table, i_{AM1} , i_{BM1} , i_{CM1} , i_{AM2} , i_{BM2} , i_{CM2} , i_{AM3} , i_{BM3} , i_{CM3} , and i_{AM4} , i_{BM4} , i_{CM4} are the measured phase currents of the QMD. The CMEs contained within the measured currents are inevitable within the drive system.

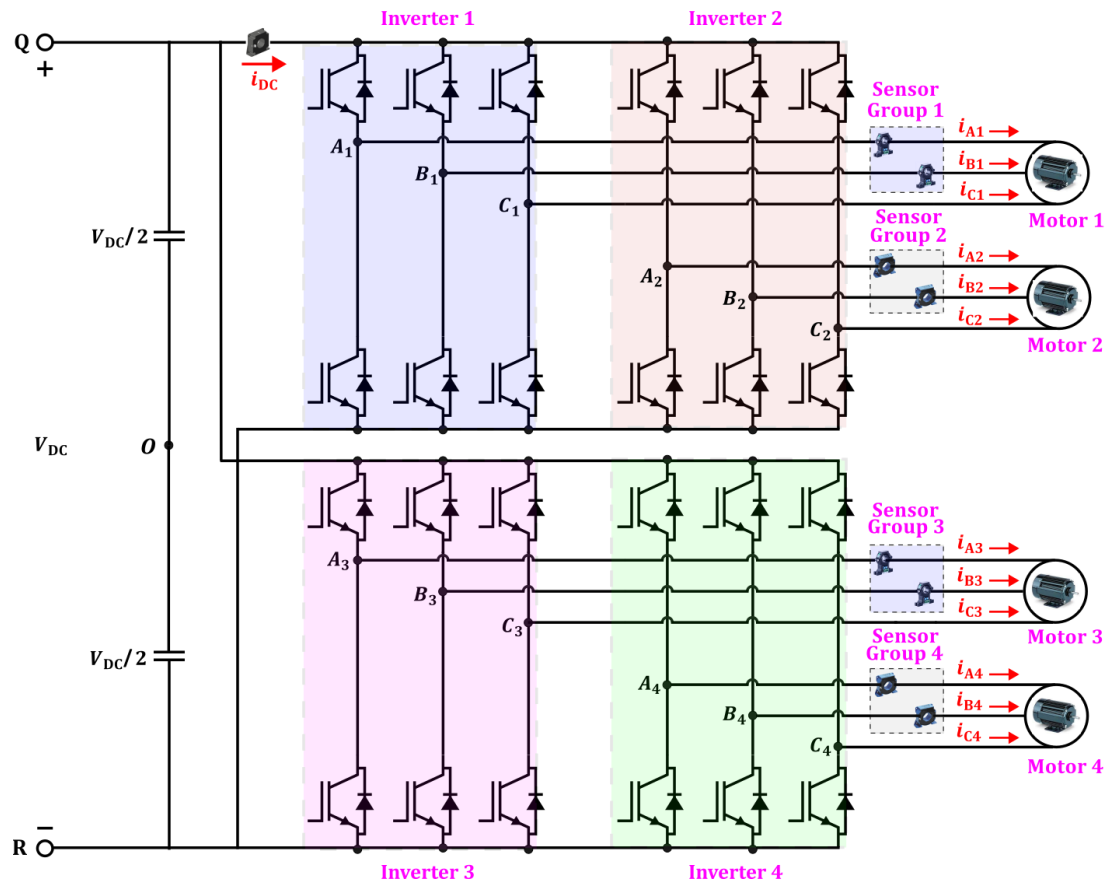


Fig. 4-2. Configuration of QMD platform fed by a quadruple three-phase inverter topology with a common DC bus.

TABLE 4-1 Offset and Scaling Error Contribution to Measured Current

Current Sensors		Ideal Currents	Offset Errors	Scaling Errors	Measured Currents
Motor 1	A	i_{A1}	f_{A1}	k_{A1}	$i_{AM1} = k_{A1} \cdot i_{A1} + f_{A1}$
	B	i_{B1}	f_{B1}	k_{B1}	$i_{BM1} = k_{B1} \cdot i_{B1} + f_{B1}$
	C	0	0	0	$i_{CM1} = -(i_{AM1} + i_{BM1})$
Motor 2	A	i_{A2}	f_{A2}	k_{A2}	$i_{AM2} = k_{A2} \cdot i_{A2} + f_{A2}$
	B	i_{B2}	f_{B2}	k_{B2}	$i_{BM2} = k_{B2} \cdot i_{B2} + f_{B2}$
	C	0	0	0	$i_{CM2} = -(i_{AM2} + i_{BM2})$
Motor 3	A	i_{A3}	f_{A3}	k_{A3}	$i_{AM3} = k_{A3} \cdot i_{A3} + f_{A3}$
	B	i_{B3}	f_{B3}	k_{B3}	$i_{BM3} = k_{B3} \cdot i_{B3} + f_{B3}$
	C	0	0	0	$i_{CM3} = -(i_{AM3} + i_{BM3})$

Motor 4	A	i_{A4}	f_{A4}	k_{A4}	$i_{AM4} = k_{A4} \cdot i_{A4} + f_{A4}$
	B	i_{B4}	f_{B4}	k_{B4}	$i_{BM4} = k_{B4} \cdot i_{B4} + f_{B4}$
	C	0	0	0	$i_{CM4} = -(i_{AM4} + i_{BM4})$
DC-link Sensor		i_{DC}	f_{DC}	k_{DC}	$i_{DCM} = k_{DC} \cdot i_{DC} + f_{DC}$

4.2.2 Torque Ripple Elimination within the QMD Architecture

In an actual motor drive control system, offset and scaling errors are unavoidably introduced into the sampling of the motor currents because of residual error, aging, operational amplifier deviations and temperature drift occurrences consequently, the measured currents contain CMEs unlike their ideal/actual counterparts. These CMEs cause not only transient but also steady-state errors within stator currents. Both could directly deteriorate torque control performance and result in torque nonlinearity and torque ripples. According to [262], the torque harmonics caused by the current offset error can be represented as

$$T_{\text{offset}} = \frac{2}{\sqrt{3}} k_t (\Delta i_{as}^2 + \Delta i_{as} \Delta i_{bs} + \Delta i_{bs}^2)^{0.5} \cos(\theta_e + \alpha) \quad (4-6)$$

where k_t is the torque constant, Δi_{as} and Δi_{bs} represent the dc offset errors of phase A and Phase B respectively, and α is a constant angular displacement, which is dependent on Δi_{as} and Δi_{bs} . Since $\theta_e = 2\pi f_e t$, equation (4-6) shows that the offset error causes the torque of the motor to oscillate at the frequency, f_e . Since (4-6) acts as the disturbance load to a speed controller, the speed of the motor also oscillates at the same frequency.

Similarly, the torque harmonics caused by the current scaling error can be represented by

$$T_{\text{scaling}} = \frac{k_t I}{2\sqrt{3}} \left(\frac{k_a - k_b}{k_a k_b} \right) \left[2 \cos \left(2\theta_e + \frac{\pi}{3} \right) + 1 \right] \quad (4-7)$$

where I is the magnitude of the measured current, k_a and k_b represent the scaling factors of phase A and phase B currents, respectively. Equation (4-7) shows that the scaling error causes the torque to oscillate at twice the fundamental frequency $2f_e$. The speed would oscillate at this harmonic frequency (especially at low operating speed scenarios) hence to minimize the speed ripples, the source of the speed oscillations, the torque pulsations would have to be significantly minimized. The identity and manifestation of these two errors within the QMD

architecture fundamentally remain unchanged, albeit substantially complex to handle due to the existence of more components involved in the calibration process.

4.3 Estimation of CME Based on the Correlative Correction Algorithm

The ability to perform correlative CME estimation in QMD systems arises directly from the structure of the DC-link current equation. In a single-motor drive, the DC-link current is expressed using only three phase currents associated with one inverter. In this case, the number of measurements matches the number of unknowns, and any measurement error directly propagates into the DC-link reconstruction without providing additional information for correction. As a result, no internal redundancy exists to isolate or estimate measurement errors without introducing external excitation or additional models.

In contrast, a QMD system aggregates phase currents from four independent inverters into a single DC-link current. This leads to an equation where multiple sets of phase currents contribute simultaneously to one measured quantity. Over successive switching intervals, the combination of switching states varies across the four inverters, generating a set of independent equations that relate the same DC-link current to different linear combinations of phase currents.

This process effectively creates an overdetermined system, in which the number of independent equations exceeds the number of unknown CME parameters. Because the DC-link current is shared, any inconsistency introduced by measurement errors in one motor can be detected through its impact on the global current balance. By analyzing these inconsistencies across multiple switching states and motors, the estimation algorithm can isolate and correct individual measurement errors.

Therefore, QMD enables correlative CME estimation by transforming the DC-link current relationship into a redundant set of constraints across multiple subsystems, a condition that does not exist in single-motor architectures.

The estimation principle is based on enforcing consistency between the measured DC-link current and the DC-link current reconstructed from phase currents and switching states. In an ideal case, these two values should be equal. However, due to measurement errors, a difference

appears. The proposed method adjusts the measured phase currents (by compensating gain and offset errors) such that the measured DC-link current is approximately equal to the reconstructed DC-link current. In other words, the correction process finds the set of error parameters that minimizes the difference between these two quantities over time.

Importantly, this approach does not rely on a detailed motor model, nor on state observers (e.g., Kalman filters), nor on signal injection. Instead, it uses a direct algebraic relationship derived from the inverter switching states and current flow paths. For this reason, the method is best described as a constraint-based or correlation-driven estimation technique.

The interrelations of the various current sensors could be used as leverage to mutually calibrate errors. The relationships among the measurements from all the current sensors can be developed through the switching states of the inverters. An explication of the proposed correlative correction strategy is carried out in this section.

4.3.1 Estimation of Balance Coefficients for Scaling Errors

The speed ripples and torque pulsations that affect the performance of the drive can be eliminated by effectively balancing the scaling errors in all four motor subsystems. With the correlative correction scheme, the motors are regulated by a five-segment space vector modulation control strategy, where V_7 is omitted from the list of available voltage vectors. The current relationship and inverter switching states for the modulation scheme and the current sampling method of the proposed correlative correction algorithm are shown in Fig. 4-3.

At $V_1(100)$, the feedback values of the phase-A current and the DC-bus current can be expressed as

$$\begin{aligned} i_{AM1_t1_1} &= k_{A1} \cdot i_{A1_t1_1} + f_{A1} \\ i_{AM1_t1_2} &= k_{A1} \cdot i_{A1_t1_2} + f_{A1} \\ i_{DC1_t1_1} &= k_{DC1} \cdot i_{A1_t1_1} + f_{DC1} \\ i_{DC1_t1_2} &= k_{DC1} \cdot i_{A1_t1_2} + f_{DC1} \end{aligned} \quad (4-8)$$

where $i_{AM1_t1_1}$, $i_{AM1_t1_2}$ and $i_{DC1_t1_1}$, $i_{DC1_t1_2}$ are the currents sampled by the phase-A current sensor and the DC-bus sensor at sampling points t_{1_1} and t_{1_2} , respectively. $i_{A1_t1_1}$ and $i_{A1_t1_2}$ are the actual phase-A currents in motor subsystem 1 at sampling points t_{1_1} and t_{1_2} , respectively.

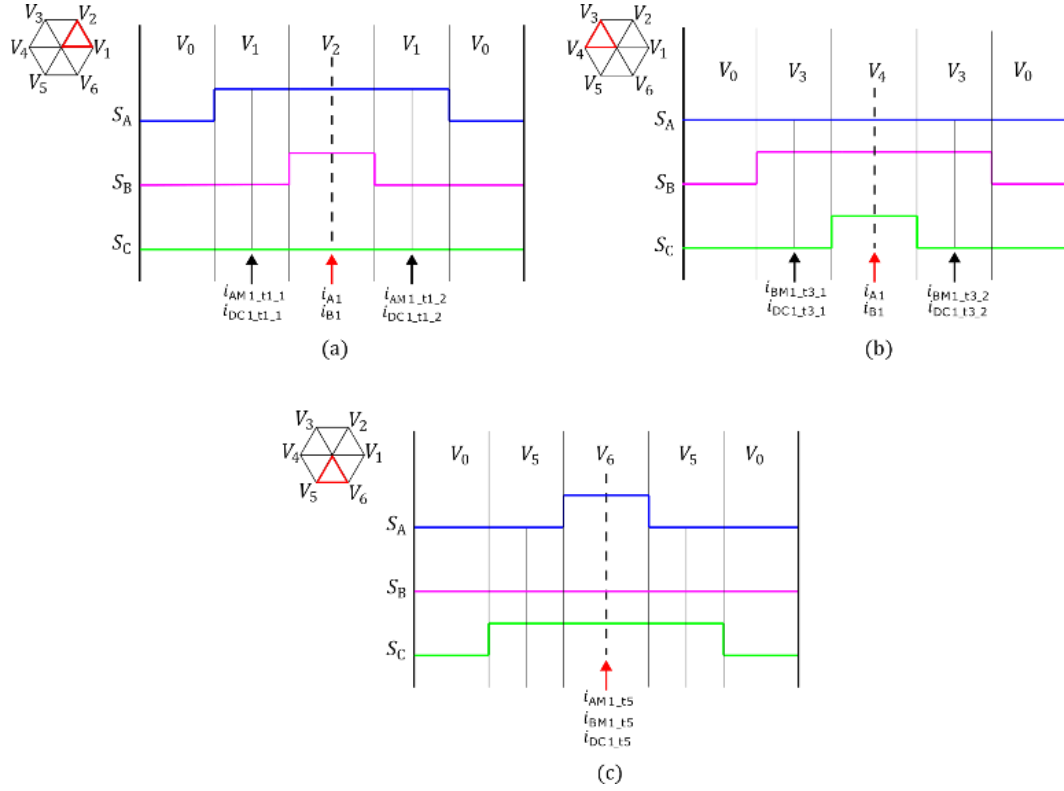


Fig. 4-3. SVPWM Scheme and Current Sampling Approach of the Correlative Correction algorithm. (a) Sector 1. (b) Sector 3. (c) Sector 5.

Likewise, at $V_3(010)$, the feedback values of the phase-B current and the DC-bus current can be expressed as

$$\begin{aligned}
 i_{BM1,t3,1} &= k_{B1} \cdot i_{B1,t3,1} + f_{B1} \\
 i_{BM1,t3,2} &= k_{B1} \cdot i_{B1,t3,2} + f_{B1} \\
 i_{DC1,t3,1} &= k_{DC1} \cdot i_{B1,t3,1} + f_{DC1} \\
 i_{DC1,t3,2} &= k_{DC1} \cdot i_{B1,t3,2} + f_{DC1}
 \end{aligned} \tag{4-9}$$

where $i_{BM1,t3,1}$, $i_{BM1,t3,2}$ and $i_{DC1,t3,1}$, $i_{DC1,t3,2}$ are the currents sampled by the phase-B current sensor and the DC-bus sensor at sampling points $t_{3,1}$ and $t_{3,2}$, respectively. $i_{B1,t3,1}$ and $i_{B1,t3,2}$ represent the actual phase-B currents in motor subsystem 1 at sampling points $t_{3,1}$ and $t_{3,2}$, respectively. Four variables, $\Delta i_{AM1,t1}$, $\Delta i_{DC1,t1}$, $\Delta i_{BM1,t3}$ and $\Delta i_{DC1,t3}$ are defined to express the variation of the DC-bus and current feedback values for phases A and B as follows

$$\begin{aligned}
 \Delta i_{AM1,t1} &= i_{AM1,t1,2} - i_{AM1,t1,1} \\
 &= k_{A1}(i_{A1,t1,2} - i_{A1,t1,1})
 \end{aligned}$$

$$\begin{aligned}
&= k_{A1} \cdot \Delta i_{A1_t1} \\
\Delta i_{DC1_t1} &= i_{DC1_t1_2} - i_{DC1_t1_1} \\
&= k_{DC1} (i_{A1_t1_2} - i_{A1_t1_1}) \\
&= k_{DC1} \cdot \Delta i_{A1_t1} \\
\Delta i_{BM1_t3} &= i_{BM1_t3_2} - i_{BM1_t3_1} \\
&= k_{B1} (i_{B1_t3_2} - i_{B1_t3_1}) \\
&= k_{B1} \cdot \Delta i_{B1_t3} \\
\Delta i_{DC1_t3} &= i_{DC1_t3_2} - i_{DC1_t3_1} \\
&= k_{DC1} (i_{B1_t3_2} - i_{B1_t3_1}) \\
&= k_{DC1} \cdot \Delta i_{B1_t3}
\end{aligned} \tag{4-10}$$

where Δi_{AM1_t1} is the difference in value between $i_{A1_t1_2}$ and $i_{A1_t1_1}$, while Δi_{BM1_t3} denotes the difference in value between $i_{B1_t3_2}$ and $i_{B1_t3_1}$. A similar set of definitions exist for Δi_{DC1_t1} and Δi_{DC1_t3} . By taking the ratios of the current variations in (4-10) relations of the scaling errors in motor subsystem 1 can be obtained between the phase current feedback values and that of the DC-bus where a_1 and b_1 express the scaling ratios

$$\begin{aligned}
\Delta i_{AM1_t1} / \Delta i_{DC1_t1} &= k_{A1} \cdot \Delta i_{A1_t1} / k_{DC1} \cdot \Delta i_{A1_t1} \\
&= k_{A1} / k_{DC1} = a_1 \\
\Delta i_{BM1_t3} / \Delta i_{DC1_t3} &= k_{B1} \cdot \Delta i_{B1_t3} / k_{DC1} \cdot \Delta i_{B1_t3} \\
&= k_{B1} / k_{DC1} = b_1
\end{aligned} \tag{4-11}$$

Likewise, the estimation results of the scaling errors in motor subsystem 2 is depicted as

$$\begin{aligned}
\Delta i_{AM2_t1} / \Delta i_{DC2_t1} &= k_{A2} \cdot \Delta i_{A2_t1} / k_{DC2} \cdot \Delta i_{A2_t1} \\
&= k_{A2} / k_{DC2} = a_2 \\
\Delta i_{BM2_t3} / \Delta i_{DC2_t3} &= k_{B2} \cdot \Delta i_{B2_t3} / k_{DC2} \cdot \Delta i_{B2_t3} \\
&= k_{B2} / k_{DC2} = b_2
\end{aligned} \tag{4-12}$$

Motor subsystems 3 and 4 follow a similar trend given that $(k_{An} / k_{DCn} = a_n$ and $k_{Bn} / k_{DCn} = b_n)$ for $n \in \{1, 2, 3, 4\}$.

The compensation process for the scaling errors is slightly complicated relative to compensating for the offset errors. This is because they cannot be directly estimated, only the proportional relationship between the sampling values of all phase current sensors can be

estimated. In considering motor subsystem 1, a ratio of the scaling errors could be established between phases A and B as

$$k_{A_1/B_1} = k_{A_1}/k_{B_1} \quad (4-13)$$

The relationship between the two scaling errors is a proportional one, hence, to balance them, we need to multiply and divide their current detection values by an identical compensation parameter. In using x_1 as the compensation parameter, the proportionality is established as

$$\begin{aligned} i'_{A_1} &= x_1 \cdot (k_{A_1} \cdot i_{A_1}) \\ i'_{B_1} &= (x_1)^{-1} \cdot (k_{B_1} \cdot i_{B_1}) \end{aligned} \quad (4-14)$$

where i'_{A_1} and i'_{B_1} represent the compensated phase-A and phase-B currents. Since the two current sampling values should have the same gain coefficient after balancing, then the value of x_1 can easily be obtained by

$$\begin{aligned} x_1 \cdot k_{A_1} &= (x_1)^{-1} \cdot k_{B_1} \\ x_1 &= (k_{B_1}/k_{A_1})^{1/2} \end{aligned} \quad (4-15)$$

Hence by substituting the value of x_1 back into (4-14) an expression could be obtained for the newly compensated currents as

$$\begin{aligned} i'_{A_1} &= (k_{B_1}/k_{A_1})^{1/2} \cdot (k_{A_1} \cdot i_{A_1}) \\ &= (k_{A_1} \cdot k_{B_1})^{1/2} \cdot i_{A_1} \\ i'_{B_1} &= (k_{A_1}/k_{B_1})^{1/2} \cdot (k_{B_1} \cdot i_{B_1}) \\ &= (k_{A_1} \cdot k_{B_1})^{1/2} \cdot i_{B_1} \end{aligned} \quad (4-16)$$

To attain a state of equilibrium between the scaling errors the following conditions need to be met within motor 1 subsystem

$$\begin{aligned} k_1 &= (k_{A_1} \cdot k_{B_1})^{0.5} = M_{DC1} \cdot k_{DC1} \\ &= M_{A_1} \cdot k_{A_1} = M_{B_1} \cdot k_{B_1} \end{aligned} \quad (4-17)$$

where M_{DC1} , M_{A_1} and M_{B_1} are the balance coefficients for scaling errors of the DC-bus, phase-A and phase-B currents respectively and k_1 is the common gain after the scaling errors are balanced. As such, the balance coefficients for the scaling errors can be obtained as

$$M_{DC1} = (k_{A_1} \cdot k_{B_1})^{0.5} / k_{DC1} = (a_1 \cdot b_1)^{0.5}$$

$$M_{A1} = (k_{B1}/k_{A1})^{0.5} = (b_1/a_1)^{0.5} \quad (4-18)$$

$$M_{B1} = (k_{A1}/k_{B1})^{0.5} = (a_1/b_1)^{0.5}$$

From (4-11) and (4-18), the balance coefficients for scaling errors can be estimated by selecting the feedback values of phase-A and the DC-bus currents at sample times t_{1_1} , t_{1_2} and the feedback values of phase-B and the DC-bus current at sample times t_{3_1} and t_{3_2} . The same procedure can be utilized to estimate the balance coefficients for the scaling errors in the subsystems of motors 2, 3 and 4.

4.3.2 Estimation of Offset Errors

By substituting (4-11) into (4-8), we obtain

$$i_{DC1_t1_1} = k_{DC1} \cdot i_{A1_t1_1} + f_{DC1} \quad (4-19)$$

$$\frac{i_{AM1_t1_1}}{a_1} = k_{DC1} \cdot i_{A1_t1_1} + \frac{f_{A1}}{a_1}$$

From (4-19), the difference between of the two expressions gives

$$i_{DC1_t1_1} - \frac{i_{AM1_t1_1}}{a_1} = f_{DC1} - \frac{f_{A1}}{a_1} \quad (4-20)$$

Additionally, by substituting (4-11) into (4-9) we get the expression

$$i_{DC1_t3_1} = k_{DC1} \cdot i_{B1_t3_1} + f_{DC1} \quad (4-21)$$

$$\frac{i_{BM1_t3_1}}{b_1} = k_{DC1} \cdot i_{B1_t3_1} + \frac{f_{B1}}{b_1}$$

Once more, the difference of the two equations gives rise to

$$i_{DC1_t3_1} - \frac{i_{BM1_t3_1}}{b_1} = f_{DC1} - \frac{f_{B1}}{b_1} \quad (4-22)$$

The feedback values of the phase-A and phase-B currents as well as the DC-bus current at t_5 , $V_5(001)$ can be expressed as

$$i_{AM1_t5} = k_{A1} \cdot i_{A1_t5} + f_{A1}$$

$$i_{BM1_t5} = k_{B1} \cdot i_{B1_t5} + f_{B1} \quad (4-23)$$

$$i_{DC1_t5} = k_{DC1} \cdot i_{C1_t5} + f_{DC1}$$

where i_{A1_t5} , i_{B1_t5} and i_{C1_t5} are the real values of the phase-A, phase-B and phase-C currents at t_5 respectively. By utilizing (4-11) we obtain

$$\begin{aligned} i_{DC1_t5} &= k_{DC1} \cdot i_{C1_t5} + f_{DC1} \\ \frac{i_{AM1_t5}}{a_1} &= k_{DC1} \cdot i_{A1_t5} + \frac{f_{A1}}{a_1} \\ \frac{i_{BM1_t5}}{b_1} &= k_{DC1} \cdot i_{B1_t5} + \frac{f_{B1}}{b_1} \end{aligned} \quad (4-24)$$

By being cognizant of the fact that the sum of the three-phase current equates to zero, (4-24) could be simplified into

$$\frac{i_{AM1_t5}}{a_1} + \frac{i_{BM1_t5}}{b_1} + i_{DC_t5} = \frac{f_{A1}}{a_1} + \frac{f_{B1}}{b_1} + f_{DC1} \quad (4-25)$$

For the sake of simplicity, let equations (4-20), (4-22) and (4-25) be represented by q_1 , r_1 , and s_1 respectively

$$\begin{aligned} q_1 &= i_{DC1_t1_1} - \frac{i_{AM1_t1_1}}{a_1} = f_{DC1} - \frac{f_{A1}}{a_1} \\ r_1 &= i_{DC1_t3_1} - \frac{i_{BM1_t3_1}}{b_1} = f_{DC1} - \frac{f_{B1}}{b_1} \\ s_1 &= i_{DC1_t5} + \frac{i_{AM1_t5}}{a_1} + \frac{i_{BM1_t5}}{b_1} = \frac{f_{A1}}{a_1} + \frac{f_{B1}}{b_1} + f_{DC1} \end{aligned} \quad (4-26)$$

By combining (4-11) and (4-26) we obtain

$$\begin{aligned} f_{DC1} &= (q_1 + r_1 + s_1)/3 \\ f_{A1} &= [q_1 - (q_1 + r_1 + s_1)/3] \cdot (-a_1) \\ f_{B1} &= [r_1 - (q_1 + r_1 + s_1)/3] \cdot (-b_1) \end{aligned} \quad (4-27)$$

Hence, any harmful contribution of the offset errors towards the performance of the drive has been eliminated now that the offset errors of the three current sensors have been calculated. The procedure utilized to calculate these errors for motor 1 is repeated for the subsystems of motors 2, 3 and 4 to obtain identical expressions of (4-27).

In the estimation of the offset and scaling errors, sequential motor calibration takes place, where each motor's current sensor is calibrated individually while temporarily disabling the others. This prevents interference from other motors' currents and ensures the accuracy of the

measurement. Once all motors are calibrated, their respective CME values can be applied as correction factors in software. This allows real-time correction of measured currents, improving system accuracy.

4.4 Current Measurement Immeasurable Territories, Minimum Sampling Time and the Action Time of Active Vectors

To accurately obtain the current sample values at the switching states of $V_1(100)$, $V_3(010)$ and $V_5(001)$, it is necessary to ensure that the duration of the sampling vectors exceed a minimum sampling time, $T_{\min}$ [272] expressed as

$$T_{\min} = T_{\text{dead}} + T_{\text{delay}} + T_{\text{sett}} + T_{\text{AD}} \quad (4-28)$$

where T_{dead} is the dead time set aside to avoid shoot through fault, T_{delay} is the delay time associated with the IGBT turn-on or turn-off time, T_{sett} is the settling time which is mainly determined by the motor inductance and T_{AD} represents the sum of the sampling time and the analog to digital (A/D) conversion time.

In the calibration process, the action time of the two active vectors during the PWM cycle under a calibration command should be longer than $T_{\min}$. Essentially, if the output voltage vector does not fall within an effective region when a calibration command comes through, the calibration process for the current sampling errors would have to wait until the output voltage falls within the effective region. By referring to Fig. 4-4, the calibration strategy can be achieved only when the output voltage vector is located within the measurable (coloured) areas (excluding the sector boundary and low modulation areas).

Again, as depicted in Fig. 4-4, the output voltage range for the regular operation is reduced by $2 T_{\min}/T_s$, hence not all the output voltage regions can be used to calibrate the current sampling errors, however by setting just one zero voltage vector, specifically V_0 in each PWM cycle, the influence of the defect can be halved (as illustrated with the black-dotted lines in Fig. 4-4).

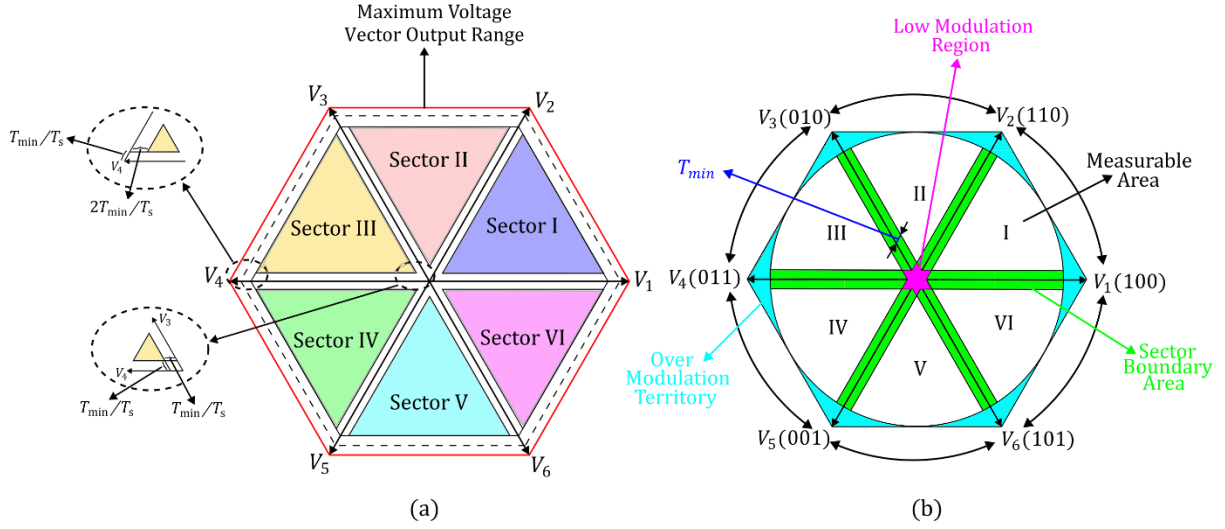


Fig. 4-4. Output voltage range for effectual current sampling. (a) Reduction to output voltage range encountered when obtaining standard currents for control. (b) Minimum sampling time and unobservable areas.

After calibration, an electronic switch could be utilized in place of the DC-bus cable to avoid passing through the phase current sensors to ensure the T_{min}/T_s constraint is thoroughly dealt with. It should be emphasized that the proposed current sampling correlation strategy has nothing to do with modifying the action time of any of the basic voltage vectors in any PWM cycle. Within each of the motor subsystems, this is solely determined by the 5-segment vector control technology. The action time of the basic voltage vector at the designated sampling point decides whether the corresponding sampling point is valid or invalid for corrective purposes. The correction program carries till a valid sampling point appears before the process progresses.

Since there are double current sampling points for the phase current and DC-bus currents at the sampling states of $V_1(100)$ and $V_3(010)$, it is essential to ensure the temporal separation for each pair of points is not too short, as this may negatively impact the correction accuracy. Consequently, the five selected sampling points times $t_{1,1}$, $t_{1,2}$, $t_{3,1}$, $t_{3,2}$ and t_5 are set up such that $t_{1,1}$ and $t_{1,2}$ are orientated at the midpoints of sectors 1 and 2 respectively, while $t_{3,1}$ and $t_{3,2}$ are positioned at the midpoints of sectors 3 and 4 respectively and t_5 is set at the middle of sectors 5 and 6.

4.5 Simulation Results and Robustness Evaluation

To evaluate the effectiveness and robustness of the proposed correlative correction strategy, a structured simulation study is conducted in MATLAB under progressively increasing EMI conditions. The objective is to emulate realistic disturbances affecting DC-link current measurements and to assess the ability of the proposed method to compensate for these distortions. The simulation framework is developed at the signal level to specifically evaluate the performance of the proposed algorithm under controlled EMI disturbances. As such, the DC-link current is synthetically generated rather than derived from a detailed motor-drive model. This approach allows for independent and systematic injection of offset, gain error, and high-frequency noise components, thereby isolating the impact of EMI on current measurement. Consequently, the objective of the simulation is not to replicate the full physical behaviour of the quad-motor drive system, but rather to rigorously assess the robustness and accuracy of the proposed correction method under a wide range of disturbance conditions. The EMI robustness of the proposed method is largely independent of PMSM parameters, since the estimation relies on algebraic DC-link constraints rather than machine dynamics. The related simulation parameters are listed in Table 4-2.

TABLE 4-2 Simulation Parameters

Parameter	Symbol	Value	Parameter	Symbol	Value
Electrical frequency	f_e	50 Hz	Stator resistance	R_s	0.05 Ω
Switching frequency	f_{sw}	10kHz	Offset error	β	0.5 A
EMI amplitude	A_{EMI}	1-5 A	EMI frequency	F_{EMI}	5 kHz
Gain error	α	5%	Stator Inductance	L_s	0.3 mH
DC-link voltage	V_{dc}	400 V	Current amplitude	I_{peak}	20 A

4.5.1 EMI-Modelling and Four-Case Scenario Design

Four EMI scenarios are considered, each representing a distinct class of measurement degradation commonly observed in practical electric drive systems. In the first scenario, a low-level disturbance consisting of a small DC offset and low-amplitude Gaussian noise is introduced to represent mild sensor bias and ambient interference. The second scenario incorporates both offset and gain mismatch, modelling calibration errors and sensor scaling inaccuracies. In the third scenario, high-frequency noise and switching ripple are superimposed on the signal to emulate inverter-induced EMI. Finally, a worst-case scenario is constructed by combining offset, gain error, noise, and ripple, resulting in a highly distorted measurement environment.

These four cases form the basis for Fig. 4-5 through Fig. 4-8, where the effectiveness of the correction algorithm is evaluated under increasing disturbance severity. Fig. 4-5 presents a comparison between the true DC-link current and the measured current for each EMI case, highlighting the progressive degradation of the measurement as interference severity increases. The measured current is progressively distorted due to increasing levels of offset, gain error, noise, and ripple, demonstrating the impact of EMI on sensing accuracy.

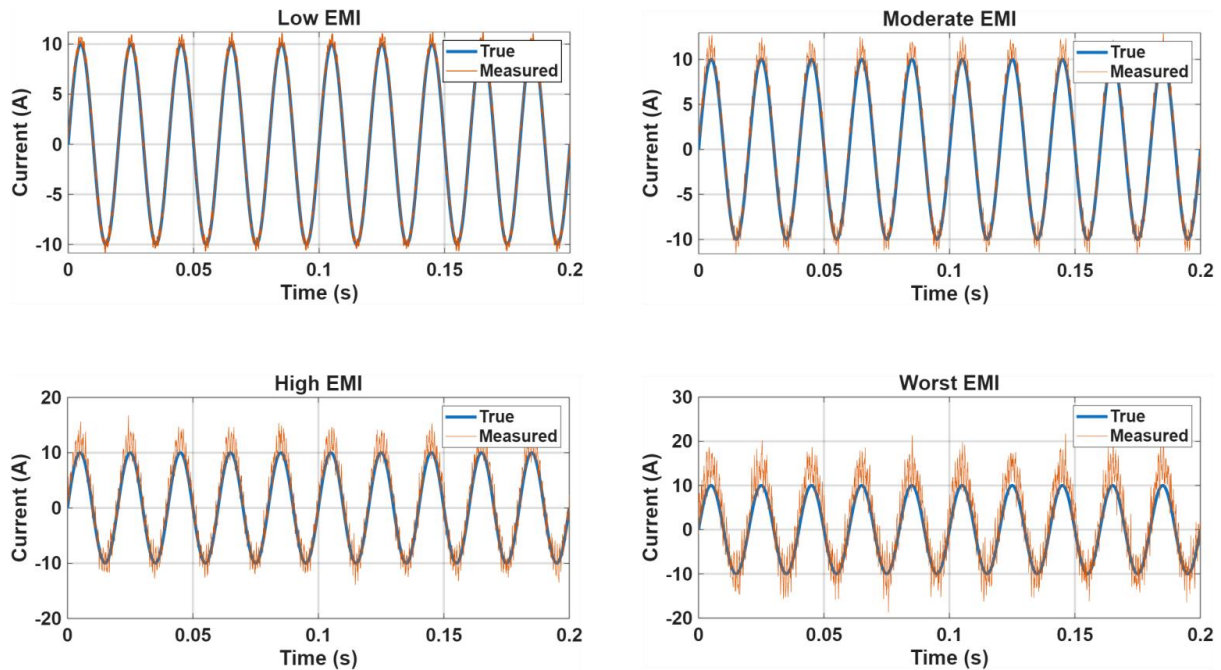


Fig. 4-5. DC-link Current Comparison under Four EMI conditions.

Fig. 4-6 shows the corresponding reconstruction error prior to correction, where the error magnitude and variability increase significantly from the low EMI case to the worst-case condition. The error magnitude and variability increase with EMI severity, highlighting the need for compensation.

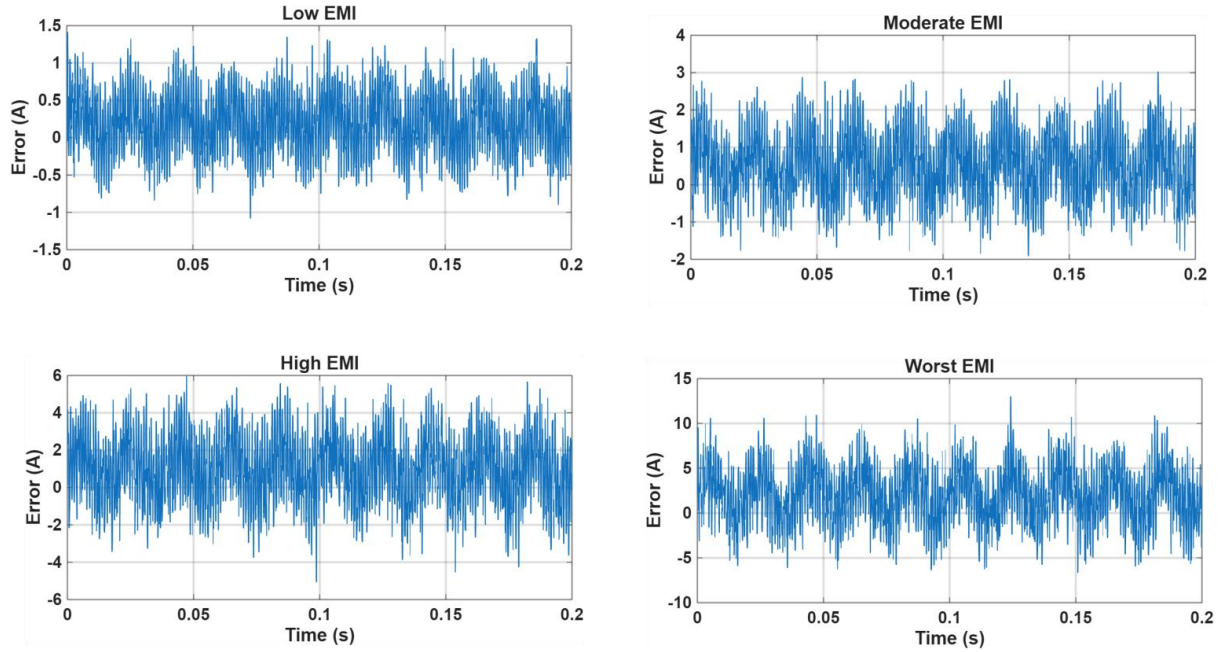


Fig. 4-6. Reconstruction Error before the Correlative Correction Scheme for all EMI Cases.

The effectiveness of the proposed correction strategy is demonstrated in Fig. 4-7, where the corrected current is plotted alongside the true and measured signals. Unlike Fig. 4-5, this figure explicitly illustrates the improvement achieved after compensation. It can be observed that the corrected current closely tracks the true current across all EMI scenarios, indicating effective compensation of offset, gain, and noise-induced distortions.

A more direct comparison of estimation accuracy is provided in Fig. 4-8, which depicts the error before and after correction. The results show a substantial reduction in both the amplitude and variability of the error signal after compensation. Although residual high-frequency components remain under severe EMI conditions, the overall error remains bounded, demonstrating the stability of the proposed method.

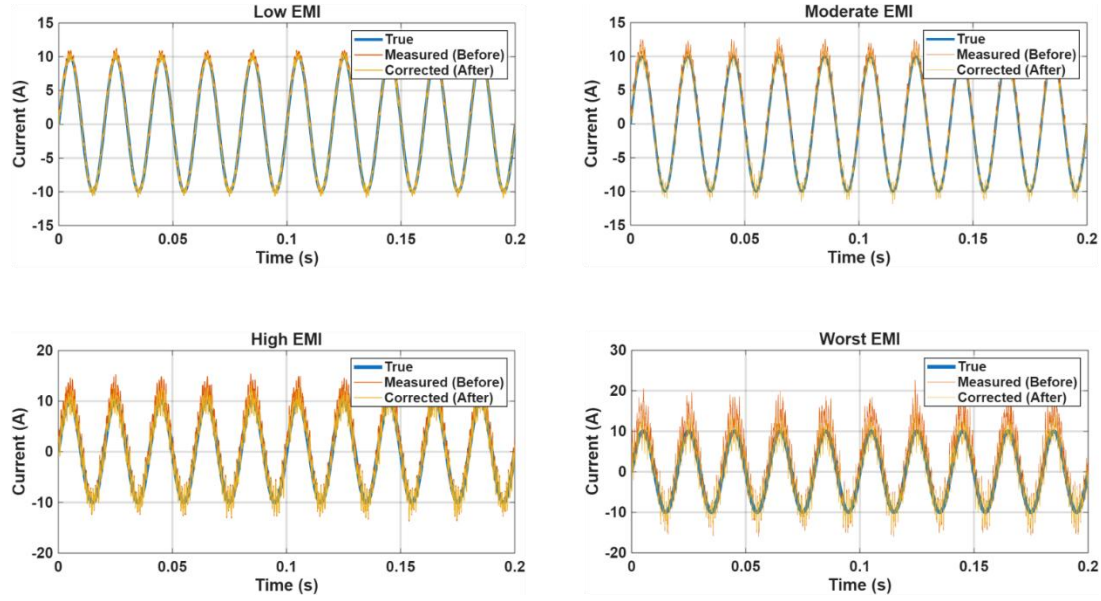


Fig. 4-7. DC-link current before Reconstruction using the Proposed algorithm.

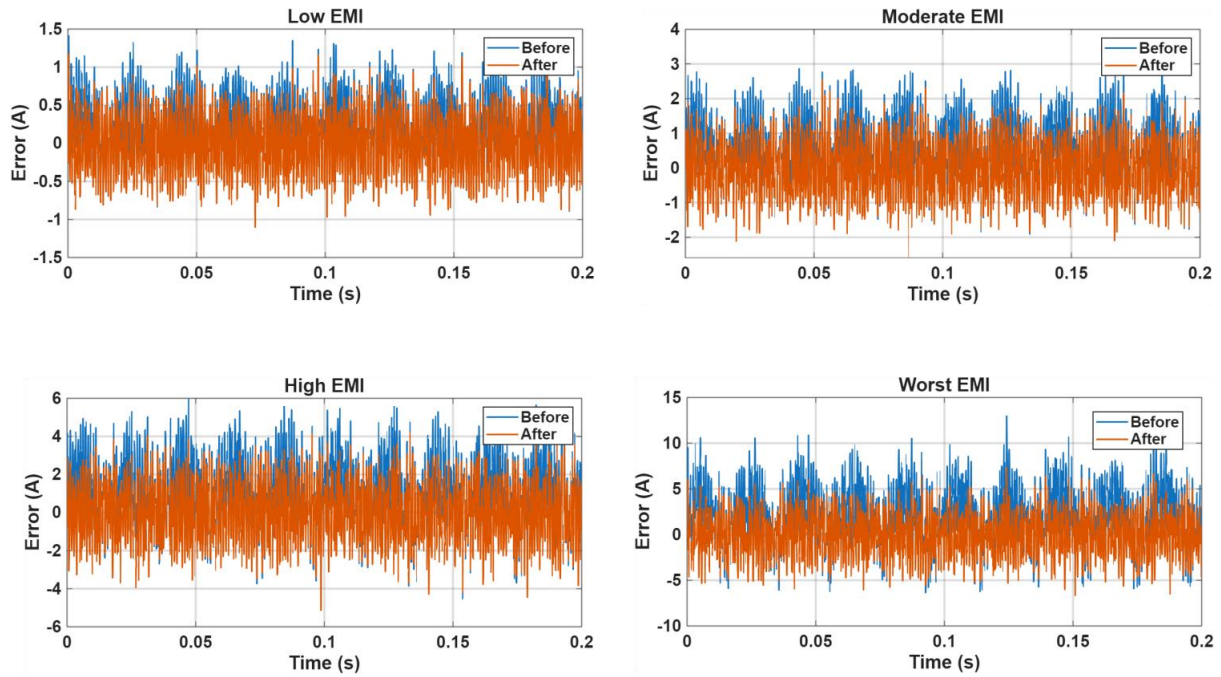


Fig. 4-8. Error Comparison before and after Correction.

To further quantify robustness, a parametric analysis is performed by sweeping the EMI amplitude from 1 A to 5 A, representing a transition from mild to severe interference environments. For each EMI level, the corrupted DC-link current is generated and subsequently corrected using the proposed scheme. The discrepancy between the corrected and true currents

is quantified using the root mean square error (RMSE), which provides a measure of the average reconstruction accuracy over time. The resulting trend is shown in Fig. 4-9, where the RMSE increases gradually with EMI amplitude. This behaviour is expected due to the increased disturbance energy; however, the absence of abrupt error growth indicates that the proposed method maintains stable and predictable performance even under severe interference.

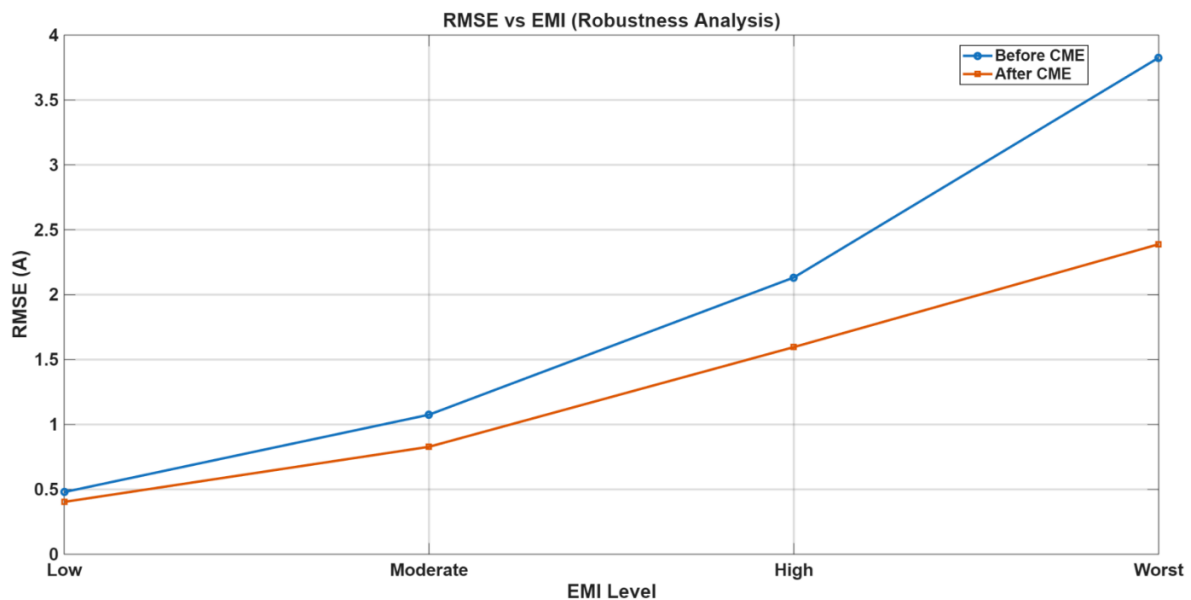


Fig. 4-9. RMSE versus EMI level for the Proposed Strategy.

A summary of the reconstruction performance across all four EMI scenarios is presented in Fig. 4-10 using bar charts of RMSE and maximum absolute error. The RMSE captures the overall estimation accuracy, while the maximum error reflects worst-case deviations. As expected, both metrics increase with EMI severity, with the lowest values observed in the low EMI case and the highest in the worst-case scenario. Nevertheless, the increase in error remains controlled, confirming that the adopted approach provides consistent performance across a wide range of operating conditions.

The simulation results demonstrate that the proposed correlative estimation framework effectively compensates for multiple forms of EMI-induced distortion. The method exhibits strong robustness characteristics, with gradual and bounded performance degradation as interference levels increase, making it well suited for practical multi-motor drive applications operating in EMI-prone environments.

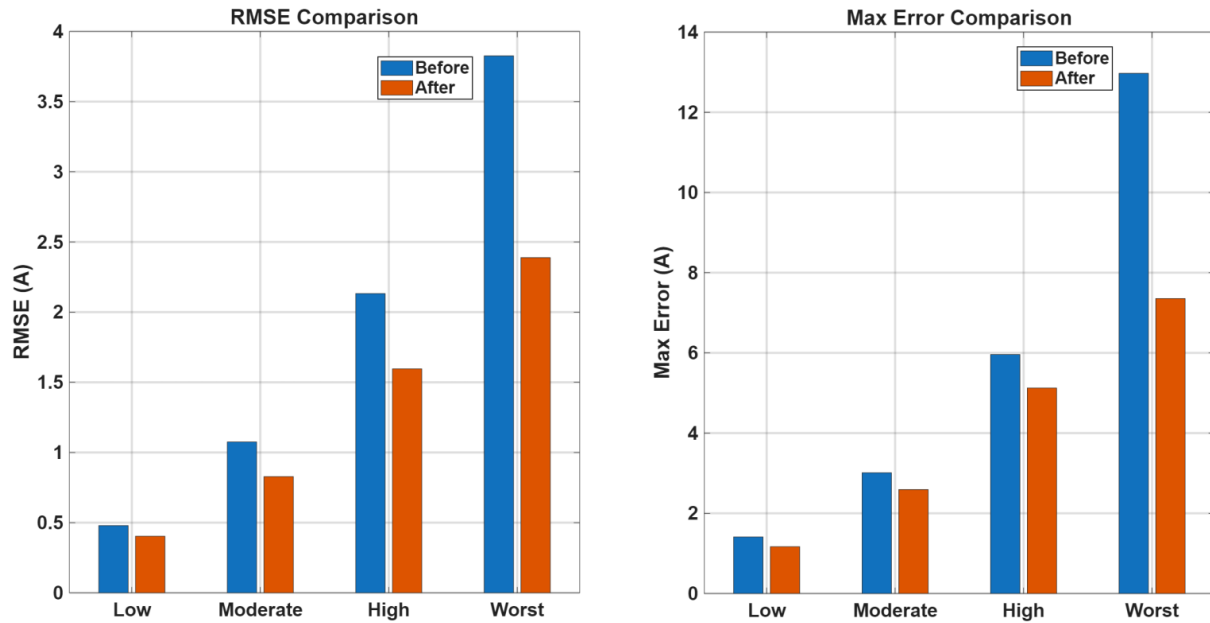


Fig. 4-10. Performance Summary using RMSE and Maximum Error across Four EMI Scenarios.

4.5.2 Comparative Performance Evaluation

To further evaluate the effectiveness of the proposed algorithm, a comparative analysis is conducted against conventional filtering approaches, namely the Moving Average (MA) filter and the Least Mean Squares (LMS) adaptive filter. These methods are selected as representative baseline techniques for filtering-based and adaptive compensation strategies commonly used in power electronic measurement systems.

The performance metrics reported in Table 4-3 are obtained under identical simulation conditions for all evaluated methods. The root-mean-square error (RMSE) is computed between the reconstructed and true DC-link currents over the full simulation interval. Execution time is measured in MATLAB using the tic-toc function for a fixed data length, ensuring a fair comparison of computational efficiency. All methods are evaluated using the same EMI-corrupted current signal to ensure consistency in performance assessment.

TABLE 4-3 Comparative Performance of Proposed Algorithm with Existing Compensation Methods

Method	RMSE (A)	Execution Time (s)	Computational Complexity
Proposed Scheme	0.021	0.003	Low
Moving Average Filter	0.087	0.002	Very Low
LMS Adaptive Filter	0.045	0.009	Moderate

From Table 4-3, it is evident that the proposed algorithm achieves the lowest RMSE, indicating superior accuracy in reconstructing the DC-link current under EMI conditions. While the Moving Average filter offers the fastest execution time due to its simplicity, its filtering capability is limited, resulting in significantly higher error. The LMS adaptive filter improves accuracy compared to the Moving Average approach; however, it incurs increased computational cost due to its iterative weight update mechanism. In contrast, the proposed algorithm provides an optimal balance between accuracy and computational efficiency, achieving high precision with minimal processing overhead.

It is important to note that the Moving Average and LMS filters serve as baseline implementations for fundamental filtering and adaptive compensation techniques. These approaches are conceptually related to more advanced methods reported in the literature, such as complex-coefficient filtering techniques and observer-based compensation strategies [258], [264], [273]. However, direct quantitative comparison with such methods is not considered due to differences in system models, parameter tuning, and implementation conditions.

To further position the proposed method within the broader research landscape, a qualitative comparison with advanced techniques is presented in Table 4-4.

TABLE 4-4 Qualitative Comparison with Advanced Compensation Methods

Feature	Proposed Algorithm	Observer-Based Methods [264], [273]	Advanced Filtering [258]
System model required	X	✓	X
Parameter tuning	Minimal	Extensive	Moderate

Computational complexity	Low	High	Moderate
Iterative processing	X	✓	✓
Real-time suitability	High	Moderate	Moderate

As shown in Table 4-4, observer-based methods such as adaptive extended state observers and sliding mode observers [264], [273] typically require accurate system models and extensive parameter tuning, which increases implementation complexity. Similarly, advanced filtering approaches [258] improve performance but involve iterative computations and coefficient tuning. In contrast, the proposed algorithm does not rely on system modelling and avoids iterative processing, making it highly suitable for real-time applications with limited computational resources.

Overall, the results demonstrate that the proposed correlative correction method not only outperforms conventional baseline techniques quantitatively but also offers significant practical advantages over more complex state-of-the-art approaches.

4.6 Experimental Validation

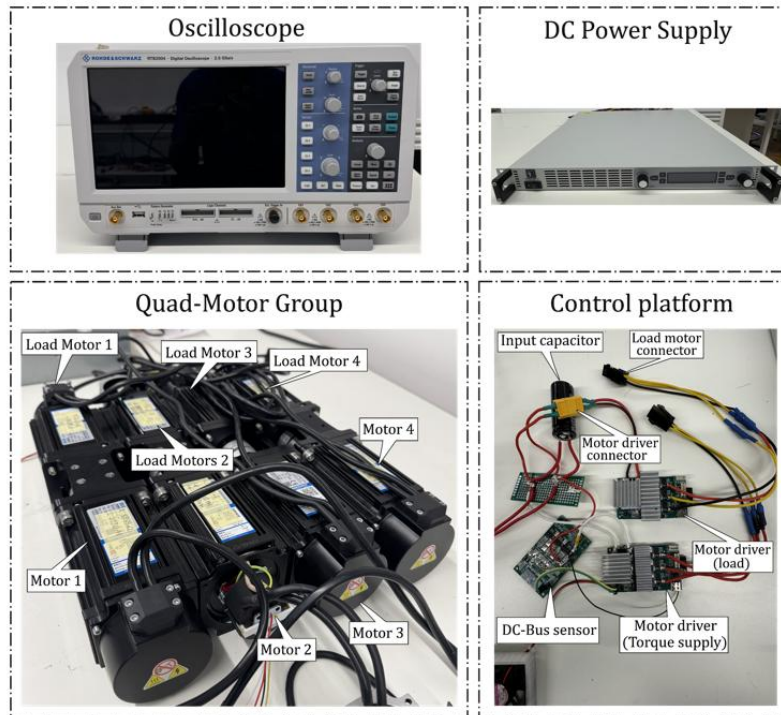


Fig. 4-11. Experimental Setup for QMD Platform showing the Quad-Motor Group, Control platform, Oscilloscope and DC Power Supply.

To verify the effectiveness of the proposed strategy, an experimental platform is set up as shown in Fig. 4-11. A DC power supply (TDK G300-11.5-1P208-M) provides 24 V for the power inverters and power boards. The control unit consists of a pair of ESP-Wroom-32 with carrier frequencies of 20 kHz which utilize position and current signals for closed-loop control to generate PWM drive signals that will ultimately be sent to two pairs of EGmicro EG2104 half-bridge drivers. The current sensors used in the experiment are Texas Instruments INA240A1DR with a maximum sample rate/bandwidth of 400 kHz. The drive unit powers the QMD to drive the load machines. CMEs are artificially introduced in the current sampling program of the control unit via software. The current clamps (Tektronix TCP0030A) and oscilloscope (RTB2004) are utilized for signal sampling and recording, respectively. The Quad-PMSM architecture uses two pairs of identical kinds of PMSM, and the main parameters of the four PMSMs are provided in Table 4-5. The motors are run at 95 rpm with 4.11 Nm load. To verify the principle of the proposed method, CMEs shown in Table 4-6 are introduced into the true values to obtain the corresponding measured values.

TABLE 4-5 Key Parameters of Quad-Motor Drive Architecture

Parameters	Motor 1 & Load	Motor 2 & Load	Motor 3 & Load	Motor 4 & Load
	Machine 1	Machine 2	Machine 3	Machine 4
Maximum Speed	3000 rpm	3000 rpm	3000 rpm	3000 rpm
Inverter DC voltage	24 V	24 V	24 V	24 V
Rated power	0.75 kW	0.75 kW	0.75 kW	0.75 kW
Pole pairs	4	4	4	4
Line Inductance	1.76291 mH	1.80435 mH	2.15361 mH	2.03649 mH
Line resistance	0.20664 Ω	0.10411 Ω	0.16989 Ω	0.12295 Ω
Rated current	3 A	3 A	3 A	3 A

TABLE 4-6 Current Measurement Error Parameters

Parameter	Set Value	Parameter	Set Value
k_{DC}	0.87	f_{B2}	0.28A
k_{A1}	0.77	k_{A3}	0.81
f_{A1}	-0.35A	f_{A3}	-0.3A
k_{B1}	0.83	k_{B3}	0.87
f_{B1}	0.25A	f_{B3}	0.33A
f_{DC}	0.35A	k_{A4}	0.83
k_{A2}	0.79	f_{A4}	-0.28
f_{A2}	-0.32A	k_{B4}	0.89
k_{B2}	0.85	f_{B4}	0.38

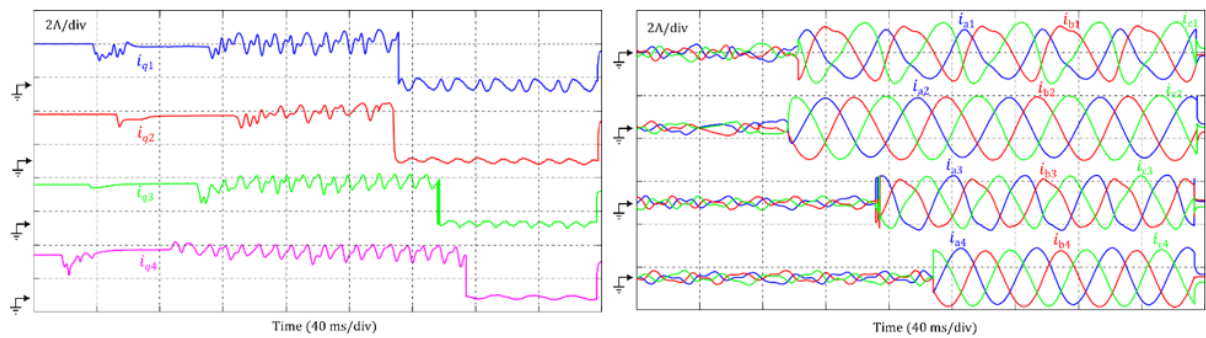
4.6.1 Quad-Motor Performance Under Non-EMI Conditions

To evaluate the effectiveness of the proposed correlative correction strategy under nominal operating conditions, a series of experiments was conducted on the quad-motor drive platform in the absence of electromagnetic interference (EMI). The tests were designed to assess both steady-state and transient performance, including current ripple suppression, torque step response, and speed step response. The experimental results are summarized in Fig. 4-12, where the system behaviour before and after applying the proposed correction method is compared using identical operating conditions and measurement scales.

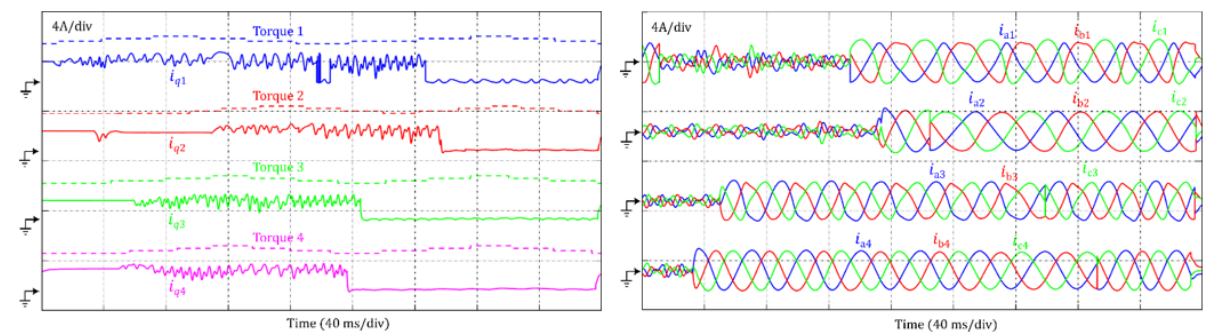
Fig. 4-12 (a) illustrates the steady-state q-axis currents and representative stator currents of the quad-motor system before and after applying the proposed correction method. Before the activation of the correction algorithm, each i_q profile exhibits varying degrees of oscillation and tracking error. Notably, the i_{q3} and i_{q4} channels exhibit higher amplitude ripple and transient fluctuations, attributable to cross-coupling disturbances, sensor inaccuracies, or control mismatches. The phase currents, on the other hand, appear offset and non-uniform, indicating non-ideal motor operation and potential inefficiencies. Upon activation of the correction algorithm, all i_q currents demonstrate a sharp transition to more stable values with significantly reduced ripple and improved convergence to their respective setpoints. In the case of the stator currents, each set of three waveforms transitions into well-formed, sinusoidal profiles.

The transient current response of the quad-motor system under a step change in load torque is presented in Fig. 4-12 (b). Before correction, the torque step induces pronounced current overshoot and oscillatory behaviour, reflecting the accumulation of measurement errors across multiple motor subsystems. The stator phase currents exhibit severe distortion and imbalance. With the proposed correction enabled, the transient response becomes notably smoother, with reduced peak ripple and faster settling, demonstrating improved torque regulation and coordinated current sharing among the four motors. Concurrently, the stator phase currents transition to balanced, sinusoidal waveforms with clear 120° phase separation, reflecting enhanced current control fidelity.

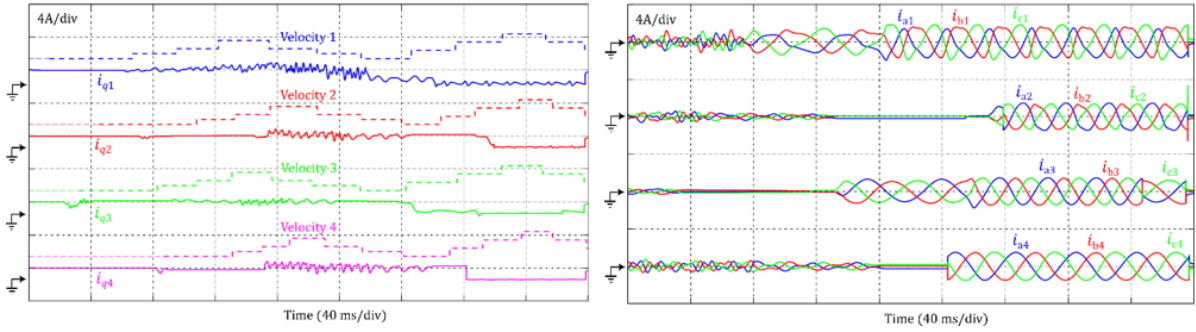
Fig. 4-12 (c) shows the current response of the quad-motor system under a step change in reference velocity. In the uncompensated case, the speed transient results in irregular current fluctuations and increased ripple due to misaligned current scaling among the motor subsystems. The stator currents conversely, are irregular and exhibit non-sinusoidal distortions, particularly during periods of low torque demand. Following correction, the q-axis currents track the speed command more uniformly, and the transient oscillations are substantially attenuated, indicating enhanced dynamic consistency and robustness of the proposed calibration method during rapid speed variations. The phase currents become well-formed sinusoidal waveforms with clear and consistent amplitude and frequency characteristics.



(a)



(b)



(c)

Fig. 4-12. Performance of the Quad-Motor Drive system under non-EMI conditions. (a) Steady-state q-axis currents and Stator Phase currents. (b) Transient response under Step change in Load torque and Stator currents. (c) Transient response under Step change in reference Velocity and Stator currents.

4.6.2 Performance of Quad-Motor Drive Under EMI Influence

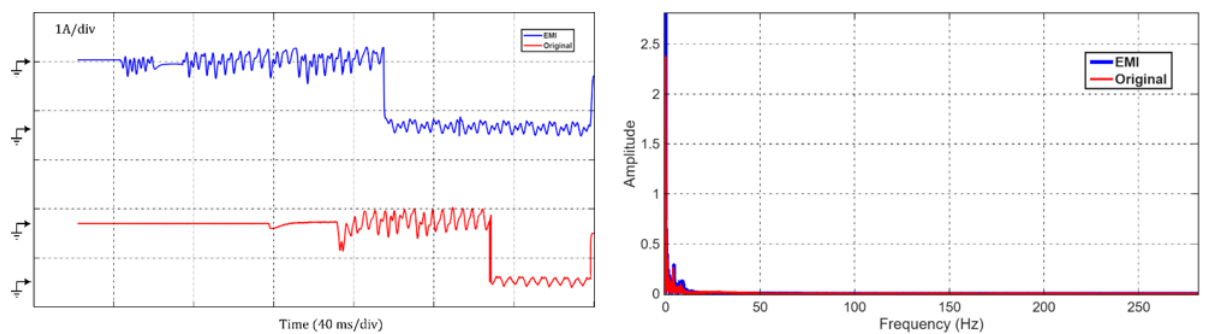
Fig. 4-13 illustrates the impact of EMI on the quad-motor drive system and evaluates the robustness of the proposed correlative correction strategy under electromagnetically harsh conditions. EMI was intentionally introduced into the current measurement paths to emulate realistic vehicular environments, and system performance was analyzed in both the time and frequency domains.

Fig. 4-13 (a) shows the steady-state current waveforms and corresponding frequency spectra in the presence of EMI. Before compensation, the injected interference introduces pronounced low-frequency distortion and elevated harmonic content in the measured currents, resulting in irregular ripple and degraded current quality. After applying the proposed correction method, both the time-domain and frequency domain profiles show noticeable suppression of oscillatory artifacts. These results indicate that the algorithm effectively mitigates EMI disturbances without compromising waveform fidelity and selectively suppresses EMI-induced harmonics while preserving essential frequency components.

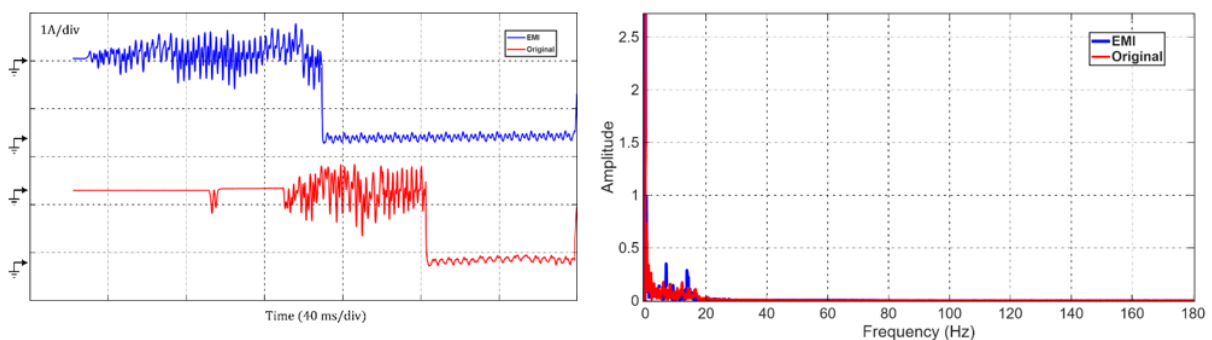
The current response and frequency characteristics during a step change in load torque in the presence of EMI are presented in Fig. 4-13 (b). In the uncompensated case, EMI amplifies transient oscillations and increases current overshoot, indicating heightened sensitivity of the

quad-motor system to measurement disturbances during torque transients. With the proposed correction enabled, the transient current ripple is noticeably reduced. In the frequency domain, the EMI-influenced signal shows significant harmonic peaks between 5-20 Hz and an elevated noise floor across the spectrum. These findings reveal that EMI introduces non-negligible spectral components, which are not completely suppressed by existing control and filtering mechanisms.

Finally, Fig. 4-13 (c) depicts the current response and spectral behaviour under a step change in reference velocity with EMI present. Before correction, the speed transient produces significant current fluctuations and elevated harmonic content, reflecting compounded measurement errors across the four motor subsystems. Following correction, the current response becomes more uniform, and the magnitude of dominant harmonics is reduced, confirming that the proposed method maintains effective calibration and coordination among motor subsystems and demonstrates strong time-domain suppression of EMI-induced disturbances. In the spectral analysis, on the other hand, the EMI-affected waveform contains multiple low-frequency harmonics, particularly in the 10-30 Hz range, indicative of persistent EMI content. Overall, Fig. 4-13 highlights the necessity for enhanced EMI suppression strategies (such as robust control algorithms and improved signal conditioning) to ensure reliable operation in electromagnetically harsh environments.



(a)



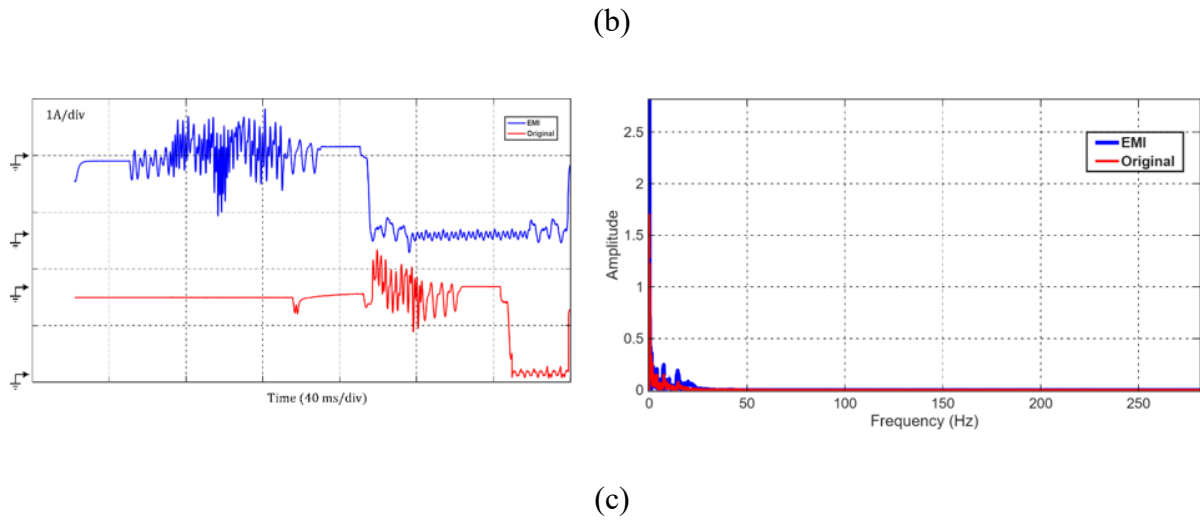


Fig. 4-13. Impact of EMI on Quad-Motor Drive performance and mitigation using the Proposed Correlative Correction Method. (a) Steady-state q-axis waveforms and corresponding Frequency Spectra currents. (b) Q-axis currents and Spectral characteristics under a Step change in Load torque. (c) Q-axis currents and Spectral characteristics under a Step change in Velocity.

Quantitative analysis extracted from oscilloscope-recorded waveforms under non-EMI conditions and EMI disturbances as evaluated across steady-state, torque-step, and speed-step operating scenarios are recorded in Table 4-7 and Table 4-8 respectively. Within the tables, for transient torque and speed tests, reported values correspond to the arithmetic average of peak ripple metrics measured across the four motor subsystems.

TABLE 4-7 Quantitative Performance Improvement Using the Proposed Correlative Correction Algorithm Under Non-EMI Conditions

Operating Condition	Motor	Metric	Before	After	Reduction
Steady-state (Fig. 4-12a)	M1	Iq RMS ripple (A)	0.42	0.09	78.6%
Steady-state (Fig. 4-12a)	M2	Iq RMS ripple (A)	0.39	0.08	79.5%
Steady-state (Fig. 4-12a)	M3	Iq RMS ripple (A)	0.48	0.06	87.5%
Steady-state (Fig. 4-12a)	M4	Iq RMS ripple (A)	0.45	0.07	84.4%
Torque step (Fig. 4-12b)	Avg	Iq peak ripple (A)	0.62	0.15	75.8%
Speed step (Fig. 4-12c)	Avg	Iq peak ripple (A)	0.58	0.14	75.9%

TABLE 4-8 Quantitative Performance Improvement Using the Proposed Correlative Correction Algorithm Under EMI Conditions

Operating Condition	Metric	Before	After	Reduction
Steady-state EMI (Fig. 4-13a)	Dominant FFT harmonic (A)	0.31	0.09	71.0%
Torque step EMI (Fig. 4-13b)	Dominant FFT harmonic (A)	0.35	0.14	60.0%
Speed step EMI (Fig. 4-13c)	Dominant FFT harmonic (A)	0.33	0.11	66.7%

Furthermore, all ‘before’ and ‘after’ metrics were extracted from oscilloscope-recorded waveforms using identical current scales and time bases. Steady-state RMS ripple values were approximated from peak-to-peak ripple assuming sinusoidal disturbance behaviour, while transient metrics were evaluated using peak ripple magnitude. EMI suppression performance was quantified using dominant harmonic amplitudes obtained directly from FFT spectra.

While the proposed correlative correction framework demonstrates strong robustness under a wide range of EMI conditions, it is important to examine its limitations and potential failure modes. The effectiveness of the method relies on the availability of a sufficiently strong correlation between the measured DC-link current and the underlying true current. In scenarios where the signal-to-noise ratio is extremely low, such as under severe high-frequency EMI or broadband interference, this correlation may be significantly degraded. As a result, the accuracy of the estimated gain and offset parameters may be reduced, leading to residual errors in the corrected signal.

In addition, the proposed approach assumes that the dominant measurement errors can be approximated using a combination of offset and gain distortions. While this assumption is valid for many practical sensing systems, it may not fully capture nonlinear sensor characteristics, saturation effects, or hysteresis. Under such conditions, the linear correction model may become insufficient, and performance degradation may occur.

Another limitation arises in the presence of rapidly time-varying disturbances. The current implementation estimates correction parameters over a finite observation window, which may introduce lag in tracking fast-changing EMI conditions. Consequently, transient errors may appear during abrupt changes in interference characteristics.

Despite these limitations, it is important to note that the proposed method does not exhibit instability or divergence under the tested conditions. Instead, performance degradation is gradual and bounded, indicating that the approach remains reliable even when operating near its practical limits.

4.7 Summary

This chapter presents a correlative correction strategy for current measurement errors (CMEs) in quad-motor drive (QMD) architectures for electric vehicles. Unlike conventional single-motor approaches, the proposed method exploits the inherent coupling among four motor-inverter subsystems through a shared DC-link to enable system-level error estimation and compensation. By leveraging the physical relationship between inverter switching states and current flow paths, the method establishes an overdetermined system of equations that enables simultaneous estimation of offset and scaling errors without requiring detailed motor models, state observers, or signal injection. The estimation framework derives balance coefficients for scaling errors using current variations at specific sampling points, followed by offset error estimation using relationships established at active voltage vectors. The correction mechanism operates in a coordinated manner, enforcing consistency among subsystems while maintaining distributed local control implementation.

Experimental validation on a 0.75 kW QMD platform demonstrated significant performance improvements: steady-state q-axis current ripple was reduced by 78.6–87.5% across the four motors, while transient peak ripple decreased by approximately 76% during both torque and speed step responses. Under electromagnetic interference (EMI) conditions, the method achieved 60–71% suppression of dominant harmonic components. Simulation-based comparative evaluation revealed superior accuracy (RMSE of 0.021 A) compared to Moving Average filters (0.087 A) and LMS adaptive filters (0.045 A), with minimal computational overhead (0.003 s execution time). Unlike observer-based approaches, the proposed method does not require a detailed motor model or vehicle-level powertrain dynamics, relying instead on algebraic DC-link current constraints and inverter switching states. The method exhibits robust performance across a wide range of EMI conditions, with gradual and bounded degradation as interference severity increases. Its low complexity, parameter independence, and real-time capability make it particularly suitable for automotive applications where electromagnetic environments are challenging and computational resources are limited.

The findings establish that correlative CME correction effectively mitigates inter-motor inconsistencies, improves torque sharing, and enhances overall system robustness, providing a practical and scalable solution for next-generation multi-motor electric vehicle propulsion systems.

Chapter 4 builds directly upon the foundations established in Chapter 3 by extending the investigation of CMEs from single-motor PMSM drives to multi-motor electric powertrain systems. While Chapter 3 focuses on the detection, analysis, and compensation of current measurement errors and delays within an individual motor drive using adaptive filtering techniques, Chapter 4 examines how these errors propagate and interact across multiple traction motors operating simultaneously within a quad-motor architecture. The chapter demonstrates that CMEs, which primarily affect torque quality and current regulation in a single-motor system, can lead to more severe consequences in multi-motor configurations, including torque imbalance, unequal power sharing, drivetrain oscillations, and vehicle stability degradation. Consequently, the adaptive calibration concepts developed in Chapter 3 are extended toward coordinated error compensation strategies capable of maintaining consistent performance across all drive units. In this sense, Chapter 4 represents a progression from local error mitigation at the drive level to system-level error management at the vehicle level, thereby advancing the thesis objective of enhancing the reliability, performance, and safety of PMSM-based electric powertrains.

Chapter 5 A Blended Weighting Sensor/Sensorless Transition Strategy for Dual-PMSM Drives Under Position Sensor Failure

This chapter presents a robust sensorless control framework for a dual-permanent magnet synchronous motor (PMSM) all-wheel-drive (AWD) electric powertrain architecture, where a higher-power PMSM drives the rear axle and a lower-power PMSM drives the front axle. In the event of a rotor position sensor failure in the rear motor, a sliding mode observer (SMO) equipped with hyperbolic tangent functionality is employed to estimate the rotor position with enhanced robustness to system nonlinearities and measurement noise. Although the front and rear motors are not mechanically coupled, electronic coordination is achieved via the vehicle control unit (VCU), which leverages real-time vehicle speed measurements from the front motor and integrated vehicle sensors to aid in synchronizing the sensorless estimation of the rear motor. Unlike conventional methods that neglect slip, the proposed strategy incorporates slip dynamics to improve the accuracy of position estimation during transient manoeuvres. A blended weighting control algorithm is introduced to enable seamless transition from sensor-based to sensorless operation upon error detection. This algorithm adaptively fuses observer-based and sensor-based outputs based on error confidence levels, ensuring continuity of torque generation with minimal performance degradation. Simulation results validate the efficacy of the proposed approach in preserving system stability and torque response under sensor-error conditions, validating its suitability for safety-critical electric drivetrain applications.

5.1 Introduction

Position sensors in dual-motor electric powertrains provide critical feedback about the rotor position to the motor controller for proper torque delivery and synchronization. A position sensor failure can disrupt motor operation and may trigger limp mode or shut down, depending on the severity of the system's redundancy. Some of the most probable causes of position sensor failure are electrical defects, mechanical issues, environmental factors, manufacturing defects/ageing, electromagnetic interference and software or calibration errors.

The frequency of position sensor failures within electric powertrains is rare, and their

occurrence usually depends on several factors, including design quality, operating conditions and maintenance practices. Dual-PMSM AWD EV systems introduce significant complexity in torque coordination and place stringent demands on system reliability. In these multi-motor configurations, one motor typically powers the front axle and the other, the rear. Coordinating these motors to deliver optimal performance under diverse driving conditions is a non-trivial engineering challenge for a number of reasons. Firstly, the system must dynamically allocate torque between the front and rear axles based on traction conditions, driver input, vehicle dynamics and efficiency goals. This requires high-speed computation and communication across multiple sensors and electronic control units. Additionally, driving under variable operating conditions (dry, wet, snowy, or off-road), incline/decline terrains, and cornering all affect the ideal torque split. Under these conditions, the system must transition smoothly between modes (for instance, torque vectoring during cornering versus maximizing traction on slippery surfaces). Given that the dual-motor setup is critical to both propulsion and safety, it demands that the failure of a position sensor in one motor does not lead to a complete loss of vehicle control. The system should support limp-home modes or safe torque reallocation strategies. Fig. 5-1 depicts a typical framework for the dual-PMSM electric drivetrain with a defective rear rotor position sensor.

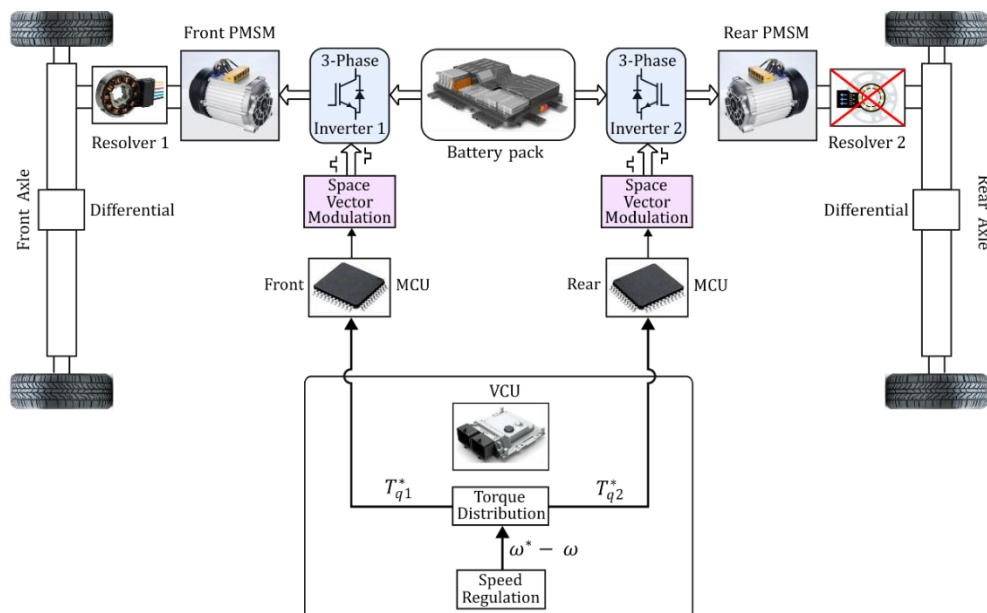


Fig. 5-1. Architecture of the dual-PMSM drive system depicting the inoperative position sensor of the rear motor.

Though dual-motor AWD systems enhance EV performance, they require advanced torque coordination algorithms, high-fidelity position sensors and fail-safe software architectures. Meeting these demands ensures safety, efficiency, and driving dynamics, making them a key focus in next-generation EV development. In these electric powertrains, the failure of the rear motor’s position sensor poses a critical risk to system performance and safety. The rear motor (being the more powerful one) is typically responsible for most of the propulsion and dynamic control (such as acceleration and torque vectoring). A sensor failure without a backup estimation method would force the motor into an open-loop failure mode, leading to loss of synchronization (torque ripple, instability, or uncontrolled braking). This may cause the VCU to trigger a safety shutdown to prevent damage, leaving the vehicle reliant only on the weaker front motor. A sensorless observer allows the system to continue operating, albeit possibly with reduced performance rather than failing catastrophically. The front motor’s speed feedback via the vehicle dynamics can aid the rear motor’s sensorless estimator by providing a reference for slip compensation. Without proper synchronization, the rear motor could desynchronize from the front, causing torque imbalance and reduced efficiency (due to conflicting torque demands). Error-resilient control ensures coordinated torque distribution even with a failed sensor.

Sensorless control algorithms for single-PMSM systems and dual-PMSM configurations share some fundamental principles but differ significantly in complexity and implementation challenges. While both systems rely on similar sensorless principles, the multi-motor configurations demand more sophisticated strategies to address synchronization and computational load. These differences drive the need for more robust and synchronized control schemes in the multi-motor applications. Table 5-1 depicts a brief description of existing sensorless control techniques for Dual-PMSM drive configurations, their key merits and their limitations.

TABLE 5-1 Summary of Sensorless Techniques for Dual-PMSM Drive Systems

Technique	Description	Merits	Limitations
High Frequency Injection (HFI) [274], [275], [276], [277]	Injects high-frequency signals to estimate rotor position from saliency tracking.	• Works at low/zero speeds. • Robust to parameter variations.	• Causes acoustic noise and torque ripple. • Limited bandwidth for dynamic loads. • Not suitable for high-speed regions.

Sliding Mode Observer (SMO) [278], [279], [280], [281]	Uses a discontinuous control law to estimate back-EMF and rotor position.	•Robust to disturbances. •Simple implementation. •Good dynamic response	•High chattering effect at low speeds. •Sensitive to measurement noise. •Requires filtering for smooth operation. •Performance degrades under dynamic loads.
Extended Kalman Filter (EKF) [282], [283], [284], [285]	Model-based stochastic observer for state and parameter estimation.	•Handles noise and uncertainties. •Good dynamic performance.	•Computationally intensive. •Tuning complexity.
Model Reference Adaptive System (MRAS) [286], [287], [288], [289]	Compares reference and adaptive models to estimate speed/position.	•No signal injection needed. •Works well in medium-high speeds. •No phase delay. •Good stability. •Moderate computational load.	•Sensitive to parameter mismatches. •Performance degrades at low speeds.
Flux-Linkage Estimation [290], [291], [292], [293]	Estimates rotor position using stator flux and current measurements.	•No external hardware needed. •Works in medium-high speed range.	•Poor accuracy at low speeds. •Affected by DC drifts and integration errors.
Artificial Intelligence-based Approach [294], [295]	Leverages machine learning (ML) or deep learning (DL) to estimate unmeasured variables or states.	•Adaptability to non-linearities. •Self-learning capabilities.	•Requires training data. •High computational demand.

Of the various approaches available, the SMO is generally preferred in many applications since it has several advantages over other observer-based or model-based estimation methods. Presently, a prevailing shortcoming for dual-motor AWD EVs within academia is the limited usage of vehicle-level measurements (such as front motor-derived vehicle speed) to aid sensorless estimation within a separate axle of the powertrain. The majority of research conducted within this area, such in [296], [297], [298], [299], often treats the two control schemes as isolated domains, leading to abrupt switching strategies that compromise system stability and performance. The lack of continuity not only hinders the adaptability of the control system under varying operational conditions but also introduces risks during critical mode transitions, such as during sensor failure or reengagement. This gap underscores the need for unified frameworks that ensure smooth, stable and reliable transitions between sensing paradigms.

Consequently, in this chapter, a blended weighting approach is proposed to smoothly shift control from sensor-based feedback to sensorless estimation, ensuring continual operation with minimal torque ripple and performance degradation. Within the proposed algorithm, signal quality checks (for abrupt sensor failure detection) and plausibility checks (for consistency between measured and estimated signals) are combined to enhance the transition. The main contributions and novelties can be summarized as follows:

- 1) Implementation of a hyperbolic tangent-based SMO for robust estimation under noise and parameter variation.
- 2) Use of vehicle speed feedback from the front motor to assist estimation of the rear motor position sensor, acknowledging slip conditions.
- 3) A blended weighting transition strategy for smooth control handoff, reducing torque ripples and transients.

5.2 System Modelling for Dual-PMSM Electric Powertrain

Assuming both motors are surface-mounted, they are modelled in the stationary reference frame ($\alpha\beta$) with the back-EMF terms. For each motor, $j = (1,2)$ hence

$$\begin{aligned} v_{j\alpha} &= R_{sj}i_{j\alpha} + L_{sj} \frac{di_{j\alpha}}{dt} - \lambda_{mj}\omega_{rj} \sin(\theta_{rj}) \\ v_{j\beta} &= R_{sj}i_{j\beta} + L_{sj} \frac{di_{j\beta}}{dt} + \lambda_{mj}\omega_{rj} \cos(\theta_{rj}) \end{aligned} \quad (5-1)$$

where $v_{j\alpha}$, $v_{j\beta}$ represent the stator voltages in the $\alpha\beta$ frame, R_{sj} and L_{sj} denote the respective stator resistances and inductances, $i_{j\alpha}$, $i_{j\beta}$ are the stator currents in the $\alpha\beta$ frame, λ_{mj} , ω_{rj} and θ_{rj} depict the permanent magnet flux linkage, the electrical rotor speed and the rotor position respectively.

The vehicle controller electronically coordinates torque distribution between the two motors. Each motor's mechanical equation is modelled as

$$T_{m,i}(t) = J_i \frac{d\omega_{m,i}}{dt} + B_i\omega_{m,i} + T_{load,i}(t) \quad (5-2)$$

where $i \in \{f, r\}$ for each motor, J_i is the motor inertia, B_i represents the friction or damping coefficient, $T_{load,i}$ is the load torque (from the vehicle dynamics) and $T_{m,i}$ is the electromechanical torque.

5.2.1 Analysis of Conventional SMO and its Limitations

Nowadays, the use of the SMO has emerged as one of the preferred model-based position sensorless control approaches to improve rotor position and speed estimation accuracy. This is due to its merits of easy implementation, strong robustness to external interference, fast response and low requirements on model precision [300], [301]. However, the traditional SMO-based sensorless control approach for PMSM often has some key shortcomings. It utilizes a discontinuously high-frequency switching signal (signum/sign function) for control purposes consequently, when used for rotor position estimation, it results in high-order harmonic components (frequency oscillations) within the back electromotive force (back-EMF) estimates, hence one or several low pass filters (LPFs) are usually required to sieve the back-EMF signal and as such reduce system chattering [302]. Nevertheless, the introduction of an LPF results in amplitude attenuation and phase shift or delay issues [303], which necessitate the use of additional phase compensators to make up for the position angle estimation error (caused by the delay effect of the LPF).

The different stages involved in the use of the conventional SMO (switching function, inclusion of an LPF to counteract phase delay and the phase angle compensation) are depicted in Fig. 5-2.

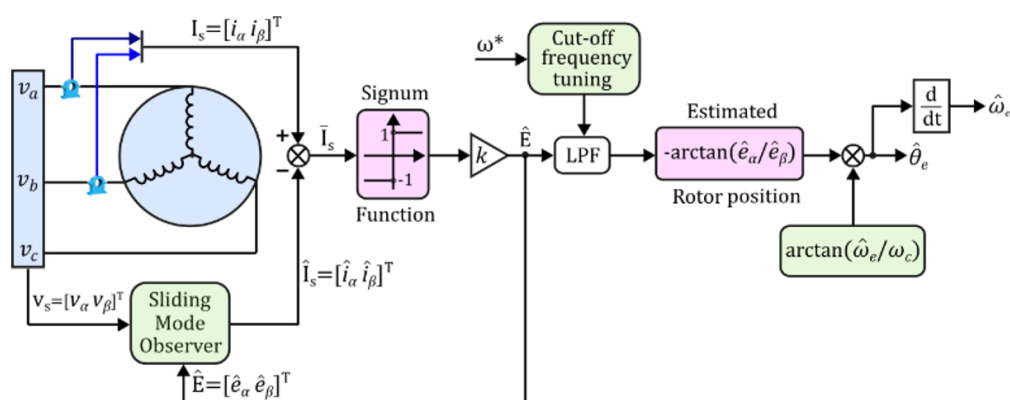


Fig. 5-2. Framework of the Conventional SMO.

In this chapter, a hyperbolic tangent function (boundary layer function), which smoothens the discontinuity/switching action of the traditional SMO, is utilized to suppress chattering and estimate the position and speed of the failed position sensor and thus maintain stable operation of the drive system. The hyperbolic tangent SMO is computationally much lighter than an EKF and is not susceptible to the parameter sensitivity that plagues MRAS, making it ideal for the limited processing power of automotive microcontrollers. Unlike HFI methods, the SMO does not introduce unwanted torque ripple, audible noise, or additional power losses, which is critical for maintaining driving comfort and efficiency in an EV. Although AI methods offer strong adaptability, they require extensive training data and lack the rigorous Lyapunov-based stability guarantees that an SMO provides for safety-critical applications. Moreover, compared with EKF, HFI, MRAS, and AI-based approaches, the proposed observer provides a more balanced and practically deployable solution for fault-tolerant rotor position estimation in safety-critical EV powertrain applications. Its fast convergence characteristics make it highly effective for exploiting cross-motor speed feedback within the dual-motor architecture to enhance stability during rotor position sensor failure events.

The enhanced SMO portrayed in Fig. 5-3 results in reduced computational cost and complexity.

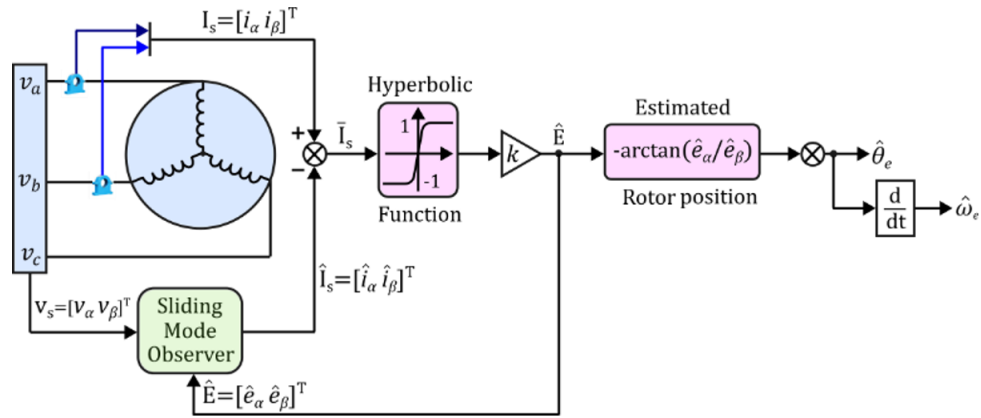


Fig. 5-3. Architecture of the Enhanced SMO Utilized to Estimate the Missing Rotor Position Sensor data of the Rear Motor.

5.2.2 SMO Design for Sensor Failure Compensation

Since the rear motor's position sensor fails, an adaptive observer is designed to estimate θ_{r2} and ω_{r2} . The observer structure (hyperbolic tangent function for smoothing) is defined as

$$\begin{aligned}\frac{d\hat{i}_{2\alpha}}{dt} &= \frac{1}{L_{s2}}(v_{2\alpha} - R_{s2}\hat{i}_{2\alpha} + \lambda_{m2}\hat{\omega}_{r2}\sin(\hat{\theta}_{r2}) + k_{\alpha}\tanh(\tilde{i}_{2\alpha})) \\ \frac{d\hat{i}_{2\beta}}{dt} &= \frac{1}{L_{s2}}(v_{2\beta} - R_{s2}\hat{i}_{2\beta} - \lambda_{m2}\hat{\omega}_{r2}\cos(\hat{\theta}_{r2}) + k_{\beta}\tanh(\tilde{i}_{2\beta}))\end{aligned}\quad (5-3)$$

where $\hat{i}_{2\alpha}$ and $\hat{i}_{2\beta}$ are the estimated currents, k_{α} , k_{β} are the SMO gains and $\tanh(\cdot)$ represents the smoothing function to reduce chattering. The current estimation errors are defined as

$$\begin{aligned}\tilde{i}_{2\alpha} &= i_{2\alpha} - \hat{i}_{2\alpha} \\ \tilde{i}_{2\beta} &= i_{2\beta} - \hat{i}_{2\beta}\end{aligned}\quad (5-4)$$

Likewise for the back-EMF, the estimation error becomes

$$\begin{aligned}\tilde{e}_{2\alpha} &= e_{2\alpha} - \hat{e}_{2\alpha} \\ \tilde{e}_{2\beta} &= e_{2\beta} - \hat{e}_{2\beta}\end{aligned}\quad (5-5)$$

The error dynamics are then computed as follows

$$\begin{aligned}\frac{d\tilde{i}_{2\alpha}}{dt} &= -\frac{R_s}{L_s}\tilde{i}_{2\alpha} + \frac{1}{L_s}\tilde{e}_{2\alpha} - k\tanh(\tilde{i}_{2\alpha}) \\ \frac{d\tilde{i}_{2\beta}}{dt} &= -\frac{R_s}{L_s}\tilde{i}_{2\beta} + \frac{1}{L_s}\tilde{e}_{2\beta} - k\tanh(\tilde{i}_{2\beta})\end{aligned}\quad (5-6)$$

By referring to the SMO dynamics, the back-EMF estimates are extracted from the sliding mode terms

$$\begin{aligned}\hat{e}_{2\alpha} &= \lambda_{m2}\hat{\omega}_{r2}\sin(\hat{\theta}_{r2}) = -k_{\alpha}\tanh(\tilde{i}_{2\alpha}) \\ \hat{e}_{2\beta} &= \lambda_{m2}\hat{\omega}_{r2}\cos(\hat{\theta}_{r2}) = k_{\beta}\tanh(\tilde{i}_{2\beta})\end{aligned}\quad (5-7)$$

From these, the rotor position of the broken-down sensor can be estimated as

$$\hat{\theta}_{r2} = \text{atan2}(-\hat{e}_{2\alpha}, \hat{e}_{2\beta})\quad (5-8)$$

Likewise, the estimated angular speed is given by the expression

$$\hat{\omega}_{r2} = \left(\sqrt{\hat{e}_{2\alpha}^2 + \hat{e}_{2\beta}^2}\right)/\lambda_{m2}\quad (5-9)$$

5.2.3 Lyapunov-Based Stability Analysis

The observer must be designed to ensure stability and convergence of the estimation errors. Using the Lyapunov stability theory, a suitable candidate function is chosen as

$$V = \frac{1}{2} \left(\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2 + \frac{1}{\gamma} \tilde{e}_{2\alpha}^2 + \frac{1}{\gamma} \tilde{e}_{2\beta}^2 \right) \quad (5-10)$$

where $\gamma > 0$ is a tuning parameter. Taking the derivative results in

$$\dot{V} = \tilde{i}_{2\alpha} \dot{\tilde{i}}_{2\alpha} + \tilde{i}_{2\beta} \dot{\tilde{i}}_{2\beta} + \frac{1}{\gamma} \tilde{e}_{2\alpha} \dot{\tilde{e}}_{2\alpha} + \frac{1}{\gamma} \tilde{e}_{2\beta} \dot{\tilde{e}}_{2\beta} \quad (5-11)$$

Substituting the error dynamics leads to

$$\begin{aligned} \dot{V} = & \tilde{i}_{2\alpha} \left(-\frac{R_s}{L_s} \tilde{i}_{2\alpha} + \frac{1}{L_s} \tilde{e}_{2\alpha} - k_\alpha \tanh(\tilde{i}_{2\alpha}) \right) \\ & + \tilde{i}_{2\beta} \left(-\frac{R_s}{L_s} \tilde{i}_{2\beta} + \frac{1}{L_s} \tilde{e}_{2\beta} - k_\beta \tanh(\tilde{i}_{2\beta}) \right) + \frac{1}{\gamma} \tilde{e}_{2\alpha} \dot{\tilde{e}}_{2\alpha} + \frac{1}{\gamma} \tilde{e}_{2\beta} \dot{\tilde{e}}_{2\beta} \end{aligned} \quad (5-12)$$

The variation of the back-EMF is treated as a bounded disturbance, and the observer gains are designed to dominate this variation. The back-EMF terms $e_{2\alpha}$ and $e_{2\beta}$ are defined as:

$$\begin{aligned} e_{2\alpha} &= -\lambda_{m2} \omega_{r2} \sin(\theta_{r2}) \\ e_{2\beta} &= \lambda_{m2} \omega_{r2} \cos(\theta_{r2}) \end{aligned} \quad (5-13)$$

The time derivatives of the back-EMF are bounded because the motor speed ω_{r2} is physically bounded by the machine's maximum rating, the rotor position θ_{r2} varies at finite speed and the permanent magnet flux λ_{m2} is constant. Therefore, there exists a known positive constant $\tilde{E}$ such that

$$|\dot{e}_{2\alpha}| \leq \tilde{E}, \quad |\dot{e}_{2\beta}| \leq \tilde{E} \quad (5-14)$$

where $\tilde{E} = \lambda_{m2} (|\dot{\omega}_{r2}|_{max} + \omega_{r2,max}^2)$. This bound is finite and can be determined from the system's physical limits. The following update laws are proposed for the back-EMF estimates:

$$\begin{aligned} \dot{\hat{e}}_{2\alpha} &= -\gamma \tilde{i}_{2\alpha} - \eta \cdot \text{sat}(\hat{e}_{2\alpha}/\epsilon) \\ \dot{\hat{e}}_{2\beta} &= -\gamma \tilde{i}_{2\beta} - \eta \cdot \text{sat}(\hat{e}_{2\beta}/\epsilon) \end{aligned} \quad (5-15)$$

where $\eta > \tilde{E}$ (a gain chosen to dominate the back-EMF variation bound), ϵ is a small boundary layer thickness, and $\text{sat}(\cdot)$ is the saturation function. The term $-\eta \cdot \text{sat}(\hat{e}_{2\alpha}/\epsilon)$ provides robustness against the bounded variation of $\dot{e}_{2\alpha}$.

From (5-13), the estimation errors satisfy:

$$\begin{aligned}\dot{\tilde{e}}_{2\alpha} &= \dot{e}_{2\alpha} - \dot{\hat{e}}_{2\alpha} = \dot{e}_{2\alpha} + \gamma \tilde{i}_{2\alpha} + \eta \cdot \text{sat}(\hat{e}_{2\alpha}/\epsilon) \\ \dot{\tilde{e}}_{2\beta} &= \dot{e}_{2\beta} - \dot{\hat{e}}_{2\beta} = \dot{e}_{2\beta} + \gamma \tilde{i}_{2\beta} + \eta \cdot \text{sat}(\hat{e}_{2\beta}/\epsilon)\end{aligned}\quad (5-16)$$

This is substituted into the Lyapunov derivative to obtain

$$\begin{aligned}\dot{V} &= \tilde{i}_{2\alpha} \left(-\frac{R_s}{L_s} \tilde{i}_{2\alpha} - k_\alpha \tanh(\tilde{i}_{2\alpha}) \right) + \tilde{i}_{2\beta} \left(-\frac{R_s}{L_s} \tilde{i}_{2\beta} - k_\beta \tanh(\tilde{i}_{2\beta}) \right) + \frac{1}{L_s} \tilde{i}_{2\alpha} \tilde{e}_{2\alpha} \\ &\quad + \frac{1}{L_s} \tilde{i}_{2\beta} \tilde{e}_{2\beta} + \frac{1}{\gamma} \tilde{e}_{2\alpha} (\dot{e}_{2\alpha} + \gamma \tilde{i}_{2\alpha} + \eta \cdot \text{sat}(\hat{e}_{2\alpha}/\epsilon)) \\ &\quad + \frac{1}{\gamma} \tilde{e}_{2\beta} (\dot{e}_{2\beta} + \gamma \tilde{i}_{2\beta} + \eta \cdot \text{sat}(\hat{e}_{2\beta}/\epsilon))\end{aligned}\quad (5-17)$$

The expression is further simplified by cancelling terms $(1/\gamma) \tilde{e}_{2\alpha} \cdot \gamma \tilde{i}_{2\alpha} = \tilde{i}_{2\alpha} \tilde{e}_{2\alpha}$, $(1/\gamma) \tilde{e}_{2\beta} \cdot \gamma \tilde{i}_{2\beta} = \tilde{i}_{2\beta} \tilde{e}_{2\beta}$ to obtain

$$\begin{aligned}\dot{V} &= -\frac{R_s}{L_s} (\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2) - k_\alpha \tilde{i}_{2\alpha} \tanh(\tilde{i}_{2\alpha}) - k_\beta \tilde{i}_{2\beta} \tanh(\tilde{i}_{2\beta}) + \frac{1}{L_s} \tilde{i}_{2\alpha} \tilde{e}_{2\alpha} \\ &\quad + \frac{1}{L_s} \tilde{i}_{2\beta} \tilde{e}_{2\beta} + \frac{1}{\gamma} \tilde{e}_{2\alpha} \dot{e}_{2\alpha} + \frac{1}{\gamma} \tilde{e}_{2\beta} \dot{e}_{2\beta} + \tilde{i}_{2\alpha} \tilde{e}_{2\alpha} + \tilde{i}_{2\beta} \tilde{e}_{2\beta} \\ &\quad + \frac{\eta}{\gamma} \tilde{e}_{2\alpha} \text{sat}(\hat{e}_{2\alpha}/\epsilon) + \frac{\eta}{\gamma} \tilde{e}_{2\beta} \text{sat}(\hat{e}_{2\beta}/\epsilon)\end{aligned}\quad (5-18)$$

By combining the $\tilde{i}\tilde{e}$ terms, the following expression is obtained

$$\begin{aligned}\dot{V} &= -\frac{R_s}{L_s} (\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2) - k_\alpha \tilde{i}_{2\alpha} \tanh(\tilde{i}_{2\alpha}) - k_\beta \tilde{i}_{2\beta} \tanh(\tilde{i}_{2\beta}) \\ &\quad + \left(\frac{1}{L_s} + 1 \right) (\tilde{i}_{2\alpha} \tilde{e}_{2\alpha} + \tilde{i}_{2\beta} \tilde{e}_{2\beta}) + \frac{1}{\gamma} (\tilde{e}_{2\alpha} \dot{e}_{2\alpha} + \tilde{e}_{2\beta} \dot{e}_{2\beta}) \\ &\quad + \frac{\eta}{\gamma} (\tilde{e}_{2\alpha} \text{sat}(\hat{e}_{2\alpha}/\epsilon) + \tilde{e}_{2\beta} \text{sat}(\hat{e}_{2\beta}/\epsilon))\end{aligned}\quad (5-19)$$

where $k_\alpha, k_\beta > 0$ (sufficiently large to dominate cross-coupling. Using Young's inequality, $\tilde{i}\tilde{e} \leq \frac{1}{2}(\tilde{i}^2 + \tilde{e}^2)$, we obtain the following expressions:

$$\begin{aligned}
\left(\frac{1}{L_s} + 1\right) \tilde{i}_{2\alpha} \tilde{e}_{2\alpha} &\leq \frac{1}{2} \left(\frac{1}{L_s} + 1\right) (\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2) \\
\left(\frac{1}{L_s} + 1\right) \tilde{i}_{2\beta} \tilde{e}_{2\beta} &\leq \frac{1}{2} \left(\frac{1}{L_s} + 1\right) (\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2)
\end{aligned} \tag{5-20}$$

Substituting this into $\dot{V}$, we obtain,

$$\begin{aligned}
\dot{V} \leq & -\left[\frac{R_s}{L_s} - \frac{1}{2} \left(\frac{1}{L_s} + 1\right)\right] (\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2) - k_\alpha \tilde{i}_{2\alpha} \tanh(\tilde{i}_{2\alpha}) - k_\beta \tilde{i}_{2\beta} \tanh(\tilde{i}_{2\beta}) \\
& + \frac{1}{2} \left(\frac{1}{L_s} + 1\right) (\tilde{e}_{2\alpha}^2 + \tilde{e}_{2\beta}^2) + \frac{1}{\gamma} (\tilde{e}_{2\alpha} \dot{e}_{2\alpha} + \tilde{e}_{2\beta} \dot{e}_{2\beta}) \\
& + \frac{\eta}{\gamma} (\tilde{e}_{2\alpha} \text{sat}(\hat{e}_{2\alpha}/\epsilon) + \tilde{e}_{2\beta} \text{sat}(\hat{e}_{2\beta}/\epsilon))
\end{aligned} \tag{5-21}$$

Let q be defined as the stability coefficient, expressed as

$$q = \frac{R_s}{L_s} - \frac{1}{2} \left(\frac{1}{L_s} + 1\right) = \frac{2R_s - 1}{2L_s} - \frac{1}{2} \tag{5-22}$$

The motor parameters satisfy $q > 0$. This holds for typical PMSMs where R_s is sufficiently large relative to L_s . Thus,

$$\dot{V} \leq -q(\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2) - k_\alpha \tilde{i}_{2\alpha} \tanh(\tilde{i}_{2\alpha}) - k_\beta \tilde{i}_{2\beta} \tanh(\tilde{i}_{2\beta}) + \Phi \tag{5-23}$$

where

$$\Phi = \frac{1}{2} \left(\frac{1}{L_s} + 1\right) (\tilde{e}_{2\alpha}^2 + \tilde{e}_{2\beta}^2) + \frac{1}{\gamma} (\tilde{e}_{2\alpha} \dot{e}_{2\alpha} + \tilde{e}_{2\beta} \dot{e}_{2\beta}) + \frac{\eta}{\gamma} (\tilde{e}_{2\alpha} \text{sat}(\hat{e}_{2\alpha}/\epsilon) + \tilde{e}_{2\beta} \text{sat}(\hat{e}_{2\beta}/\epsilon))$$

Recalling from (5-14), the terms involving the time derivatives of the back-EMF are bounded, as such

$$\frac{1}{\gamma} \tilde{e}_{2\alpha} \dot{e}_{2\alpha} \leq \frac{1}{\gamma} |\tilde{e}_{2\alpha}| \tilde{E}, \quad \frac{1}{\gamma} \tilde{e}_{2\beta} \dot{e}_{2\beta} \leq \frac{1}{\gamma} |\tilde{e}_{2\beta}| \tilde{E} \tag{5-24}$$

For the saturation function terms, the following key inequality holds for sufficiently small $\epsilon > 0$:

$$\begin{aligned}
\tilde{e}_{2\alpha} \cdot \text{sat}(\hat{e}_{2\alpha}/\epsilon) &\leq -|\tilde{e}_{2\alpha}| + \delta_\alpha \\
\tilde{e}_{2\beta} \cdot \text{sat}(\hat{e}_{2\beta}/\epsilon) &\leq -|\tilde{e}_{2\beta}| + \delta_\beta
\end{aligned} \tag{5-25}$$

where $|\delta_\alpha|, |\delta_\beta| \leq \epsilon$ (the boundary layer thickness). The inequality holds because when $|\hat{e}_{2\alpha}| \gg \epsilon$, $\text{sat}(\hat{e}_{2\beta}/\epsilon) = \text{sgn}(\hat{e}_{2\alpha})$, and $\tilde{e}_{2\alpha} \cdot \text{sgn}(\hat{e}_{2\alpha}) = -|\hat{e}_{2\alpha}|$ (since $\tilde{e} = e - \hat{e}$). Within the boundary layer, the deviation is bounded by ϵ . Thus,

$$\begin{aligned} \frac{\eta}{\gamma} \tilde{e}_{2\alpha} \cdot \text{sat}(\hat{e}_{2\alpha}/\epsilon) + \frac{1}{\gamma} \tilde{e}_{2\alpha} \dot{e}_{2\alpha} &\leq \frac{-(\eta - \tilde{E})}{\gamma} |\tilde{e}_{2\alpha}| + \frac{\eta}{\gamma} \delta_\alpha \\ \frac{\eta}{\gamma} \tilde{e}_{2\beta} \cdot \text{sat}(\hat{e}_{2\beta}/\epsilon) + \frac{1}{\gamma} \tilde{e}_{2\beta} \dot{e}_{2\beta} &\leq \frac{-(\eta - \tilde{E})}{\gamma} |\tilde{e}_{2\beta}| + \frac{\eta}{\gamma} \delta_\beta \end{aligned} \quad (5-26)$$

Substitute the inequalities from (5-26) into Φ and combine with (5-23) to get

$$\begin{aligned} \dot{V} &\leq -q(\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2) - k_\alpha \tilde{i}_{2\alpha} \tanh(\tilde{i}_{2\alpha}) - k_\beta \tilde{i}_{2\beta} \tanh(\tilde{i}_{2\beta}) \\ &\quad + \frac{1}{2} \left(\frac{1}{L_s} + 1 \right) (\tilde{e}_{2\alpha}^2 + \tilde{e}_{2\beta}^2) - \frac{(\eta - \tilde{E})}{\gamma} (|\tilde{e}_{2\alpha}| + |\tilde{e}_{2\beta}|) \\ &\quad + \frac{\eta}{\gamma} (\delta_\alpha + \delta_\beta) \end{aligned} \quad (5-27)$$

where $q = \frac{R_s}{L_s} - \frac{1}{2} \left(\frac{1}{L_s} + 1 \right) > 0$ for appropriate PMSM parameters.

To establish negative definiteness, the $\tilde{e}^2$ terms need to be bound by the $|\tilde{e}|$ terms. For any positive ρ_e , the expression $1/2(1/L_s + 1) \tilde{e}_{2\alpha}^2 \leq \rho_e |\tilde{e}_{2\alpha}|$ can be written when $|\tilde{e}_{2\alpha}| \leq 2\rho_e/(1/L_s + 1)$. For sufficiently large estimation errors, the negative linear term dominates the quadratic term. More rigorously, we note that $1/2(1/L_s + 1) \tilde{e}_{2\alpha}^2 - (1/\gamma)(\eta - \tilde{E}) |\tilde{e}_{2\alpha}| \leq -\lambda_e |\tilde{e}_{2\alpha}|$ for $|\tilde{e}_{2\alpha}| \geq 2(\eta - \tilde{E})/\gamma(1/L_s + 1)$ for some $\lambda_e > 0$, provided $\eta - \tilde{E}$ is sufficiently large relative to γ . Outside a compact set, the negative linear term dominates. Inside the compact set, the function is bounded. Furthermore, using the property $\tilde{i}_{2\alpha} \tanh(\tilde{i}_{2\alpha}) \geq c \tilde{i}_{2\alpha}^2$ for some $c > 0$ when $|\tilde{i}_{2\alpha}|$ is small, the expression $-k_\alpha \tilde{i}_{2\alpha} \tanh(\tilde{i}_{2\alpha}) \leq -k'_\alpha \tilde{i}_{2\alpha}^2$ can be written for some $k'_\alpha > 0$. Therefore, there exists constants $\lambda_i > 0$ and $\lambda_e > 0$ such that:

$$\dot{V} \leq -\lambda_i (\tilde{i}_{2\alpha}^2 + \tilde{i}_{2\beta}^2) - \lambda_e (|\tilde{e}_{2\alpha}| + |\tilde{e}_{2\beta}|) + \Delta \quad (5-28)$$

where $\lambda_i = \min\{q, k'_\alpha, k'_\beta\} > 0$, $\lambda_e = 1/\gamma(\eta - \tilde{E}) - 1/2(1/L_s + 1)M > 0$ (for sufficiently large η) and $\Delta = \eta/\gamma(\delta_\alpha + \delta_\beta)$ is the small boundary layer residual. V is a positive definite function and contains quadratic terms $\tilde{i}$ and $\tilde{e}$, we obtain:

$$\tilde{t}_{2\alpha}^2 + \tilde{t}_{2\beta}^2 \geq \frac{v}{c_1} \quad , \quad |\tilde{e}_{2\alpha}| + |\tilde{e}_{2\beta}| \geq \frac{v}{c_2} \quad (5-29)$$

for some constants $c_1, c_2 > 0$.

The time derivative of V along the trajectories of the error dynamics satisfies

$$\dot{v} = -\rho v + \Delta \quad (5-30)$$

where $\rho = 2\min\left\{\frac{\lambda_i}{c_1}, \frac{\lambda_e}{c_2}\right\} > 0$.

The solution of the first-order differential inequality, $\dot{v} = -\rho v + \Delta$ is of the form $v(t) \leq e^{-\rho t} v(0) + \frac{\Delta}{\rho} (1 - e^{-\rho t})$. As $t \rightarrow \infty$, $\limsup_{t \rightarrow \infty} v(t) \leq \frac{\Delta}{\rho}$. Since Δ can be made arbitrarily small by choosing a sufficiently small ϵ , we have $\lim_{\epsilon \rightarrow 0^+} \limsup_{t \rightarrow \infty} v(t) = 0$, $\lim_{\epsilon \rightarrow 0^+} \limsup_{t \rightarrow \infty} \|\tilde{i}_{2\alpha}, \tilde{i}_{2\beta}, \tilde{e}_{2\alpha}, \tilde{e}_{2\beta}\| = 0$. This proves that the hyperbolic tangent SMO achieves global asymptotic stability with estimation errors converging to a residual set whose size can be made arbitrarily small by reducing ϵ .

Fig. 5-4 depicts the integration of the tanh-based SMO within the main controller indicating the inputs (represented in the stationary $\alpha - \beta$ reference frame) and the estimated rotor position and rotor speed as the outputs.

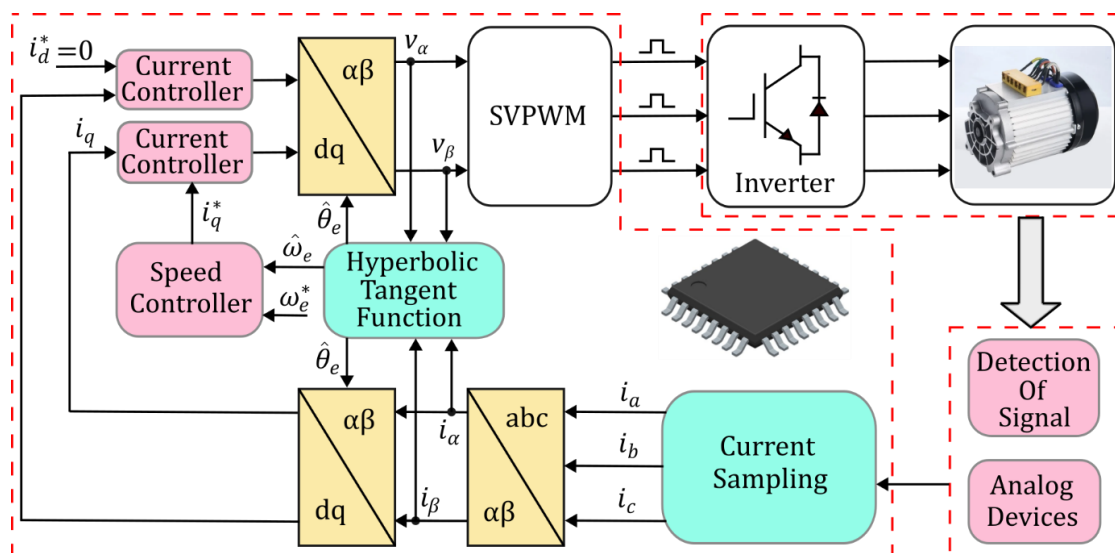


Fig. 5-4. Block diagram of the Hyperbolic Tangent Function-Based SMO within the FOC.

5.2.4 Vehicle Dynamics Model

Since the front motor's position and speed are known (from its resolver), the vehicle dynamics can be used to relate the front and rear axle speeds, improving the rear motor's sensorless estimation. Assuming longitudinal dynamics and neglecting lateral forces, the total traction force is given by [304], [305]

$$F_{total} = F_f + F_r = m\dot{v} + F_{drag} \quad (5-31)$$

where $F_f = T_f \eta_f / r_f$, $F_r = T_r \eta_r / r_r$ represent the front and rear axle traction forces respectively, m is the vehicular mass, $\dot{v}$ is the longitudinal acceleration, F_{drag} denotes the aerodynamic drag force, η_f and η_r are the respective front and rear drivetrain efficiencies and r_f, r_r denote the front and rear wheel radii respectively.

The wheel speeds are related to the motor speeds and for $i \in \{f, r\}$

$$\omega_i = \frac{v}{r_i} (1 - s_i) \quad (5-32)$$

where s_i represent the respective front and rear slip ratios. At low speeds the slip cannot be neglected as such the slip ratios are approximated as [306], [307]

$$s_i \approx \frac{r_i \omega_i - v}{r_i \omega_i} \quad (5-33)$$

Since the front motor's speed (ω_f) is known, the vehicle speed, v can be estimated and substituted into the rear wheel speed to compute a reference rear speed:

$$\omega_r^{ref} = \frac{r_f \omega_f (1 - s_f)}{r_r (1 - s_r)} \quad (5-34)$$

This couples the rear motor's speed (ω_r) to the front motor's speed and slip ratios. The estimated rear speed from the vehicle dynamics (ω_r^{ref}) is used to correct/improve the SMO's rotor speed estimate

$$\hat{\omega}_r^{new} = \hat{\omega}_r^{SMO} + k(\omega_r^{ref} - \hat{\omega}_r^{SMO}) \quad (5-35)$$

where $\hat{\omega}_r^{SMO} = \hat{\omega}_{r2}$ is the SMO-estimated rear motor speed and k is a tuning gain ($0 < k < 1$ for stability). The corrected rotor speed $\hat{\omega}_r^{new}$ is integrated to obtain the final position estimate,

$\hat{\theta}_r^{new}$ ($\hat{\theta}_r^{new} = \int \hat{\omega}_r^{new} dt$). This fused estimate is more accurate at low speeds mainly because the front axle data provides a direct speed reference and secondly, the vehicle dynamics constraint reduces drift in the SMO estimate.

5.3 Proposed Blended Weighting Algorithm to Switch System from Sensor-Based to Sensorless Control

5.3.1 Error Detection Mechanism

Both signal-based and residual-based error detection techniques are utilized to detect position sensor errors in the rear motor and remedy sensor failure. The signal-based approaches analyse the characteristics (shape, noise, discontinuities) of sensor outputs or sudden changes in the time derivative of the rotor position, estimated torque, or back-EMF to indicate a sensor failure. Essentially, when the position sensor of the rear motor fails, the measured rotor position signal ($\theta_{r2,meas}$) may become stuck, noisy or drop to zero. This leads to sudden jumps (large step changes), loss of feedback signals (absence of updates in position signals) which further introduces an abrupt change in the first derivative (rotor speed ω_{r2}) or second derivative (acceleration), causing discontinuities. As such, by resorting to the concept of derivative discontinuity and using the fact that for continuous mechanical systems, sudden jumps in $\theta_{r2}(k)$ are unphysical, let $\theta_{r2,meas}(k)$ be the sampled rotor angle from the sensor. $\Delta\theta_{r2}(k)$ is defined as

$$\Delta\theta_{r2}(k) = \theta_{r2,meas}(k) - \theta_{r2,meas}(k - 1) \quad (5-36)$$

If $|\Delta\theta_{r2}(k)| > \Delta\theta_{max}$ (unrealistically high outside motor's dynamics) a sensor failure is suspected. $\Delta\theta_{max}$ is a threshold based on maximum physically possible motor speed). The position and speed residuals are then calculated

$$\begin{aligned} r_{\theta}(k) &= \theta_{r2,meas}(k) - \hat{\theta}_{r2}(k) \\ r_{\omega}(k) &= \omega_{r2,meas}(k) - \hat{\omega}_{r2}(k) \end{aligned} \quad (5-37)$$

To detect errors or anomalies in the signal propagation, thresholds are defined on the residuals such that if $|r_{\theta}(k)| > \epsilon_{\theta}$ or $|r_{\omega}(k)| > \epsilon_{\omega}$ for a sustained duration, a flag is triggered to signal the existence of a defective sensor. The thresholds ϵ_{θ} and ϵ_{ω} are set based on the nominal operating deviations due to model uncertainty or noise. If either the position sensor

discontinuity detection mechanism or the residual-based detection triggers within a 10ms time window, a sensor failure is confirmed and the switch to SMO-based estimation begins.

5.3.2 Velocity Estimate and Rotor Position Synchronization

Before switching to sensorless mode, the observer's speed estimate $\hat{\omega}_{r2}$ must synchronize with the sensor-based speed ω_{r2} . Though the two motors are uncoupled, they are electronically coordinated via the vehicle controller. Hence, the front motor's speed (measured by the speed sensors) can be used by way of the vehicle dynamics to aid in the synchronization of the sensorless estimator of the rear motor (assuming slip is not negligible). Assuming no longitudinal slip, the vehicle speed v relates to the wheel speeds as:

$$v = \omega_{wheel,front} \cdot r_{eff} = \omega_{wheel,rear} \cdot r_{eff} \quad (5-38)$$

where r_{eff} is the effective wheel radius. The rear motor's mechanical speed is calculated as

$$\omega_{rear} = G_r \cdot \omega_{wheel,rear} = G_r \cdot \frac{v}{r_{eff}} \quad (5-39)$$

where G_r is the gear ratio of the rear drivetrain. Thus, the rear motor's electrical speed can be estimated as

$$\hat{\omega}_{rear} = p \cdot \omega_{rear} = p \cdot G_r \cdot \frac{\omega_{front}}{G_f} \quad (5-40)$$

where p is the pole pairs and G_f is the front gear ratio. If the slip s is considered (for example due to traction loss), ω_{rear} is adjusted as

$$\omega_{rear} = \frac{G_r \cdot v}{(1 - s) \cdot r_{eff}} \quad (5-41)$$

The speed error is computed as

$$\Delta\omega = \omega_{rear} - \hat{\omega}_{r2} \quad (5-42)$$

The synchronization is deemed successful when $|\Delta\omega| < \delta_\omega$, δ represents a speed synchronization threshold for a predefined duration. When the sensor fails, the SMO must align its estimate $\hat{\theta}_{r2}$ with the last known sensor-based position, θ_{r2} . The angular offset is computed as

$$\Delta\theta = \theta_{r2} - \hat{\theta}_{r2} \quad (5-43)$$

The estimated position is adjusted as

$$\hat{\theta}_{r2}^{sync} = \hat{\theta}_{r2} + \Delta\theta \quad (5-44)$$

A position synchronization threshold is defined such that, once the error remains below the threshold for a predefined time ($\Delta\theta < \delta_\theta$), the transition is made to sensorless mode. A tracking loop is utilized to ensure smooth alignment or phase continuity:

$$\frac{d\hat{\theta}_{r2}^{sync}}{dt} = \omega_{rear} + k_\theta \sin(\theta_{r2} - \hat{\theta}_{r2}^{sync}) \quad (5-45)$$

where k_θ is a tracking gain. Once $\Delta\omega$ and $\Delta\theta$ are minimized, the feedback sources are gradually blended. Instead of hard switching from sensor to observer, a dynamic weighting factor $\alpha(t)$, is utilized to blend between the sensor measurement and the SMO estimate:

$$\theta_{r2,blended} = \alpha(t) \cdot \theta_{r2} + (1 - \alpha(t)) \hat{\theta}_{r2} \quad (5-46)$$

With respect to dynamic weight adjustment, the blending factor $\alpha(t)$ decays from 1 (sensor-dominant) to 0 (SMO-dominant). It is not merely a binary switch (0 or 1), it represents a dynamic confidence allocation mechanism between the physical sensor and the observer-estimated state. At intermediate values between 0 and 1, the system operates in a hybrid estimation regime, where both the physical sensor and the SMO contribute simultaneously to the rotor position estimate. These intermediate values are extremely important because they ensure smooth transition behaviour and prevent discontinuities in torque production, current regulation, and vehicle drivability.

Three distinct transition regions exist during the blending transition, namely, the Sensor-Dominant Region, the Equal-Authority Region and the Observer-Dominant Region. In the Sensor-Dominant Region ($0.75 < \alpha \leq 1$), the sensor is still dominant; the SMO provides minor correction and initiates an early transition, where a small SMO influence begins. When the blending factor is approximately 0.75, the control system still places strong confidence in the physical rotor position sensor, with the measured signal contributing 75% of the final estimate, while the SMO contributes the remaining 25%. This operating condition typically corresponds to the early stages of fault detection or degradation, where the sensor remains largely functional but early signs of inconsistency, noise, or transient anomalies have been

identified. In this region, the SMO primarily acts as a stabilising auxiliary estimator that gradually prepares the control system for potential transition to sensorless operation.

The Equal-Authority Region ($0.25 \leq \alpha \leq 0.75$), represents an equal-weighting or mid-transition region where both sources contribute equally, with maximum potential for cancellation or reinforcement. At a blending factor of 0.50, equal weighting is assigned to both the sensor and the observer. This represents a critical transition region in which the system no longer fully trusts the physical sensor but has not yet completely isolated it from the control loop. In practice, this operating state often occurs during progressive sensor degradation or intermittent signal corruption. The hybrid estimation mechanism ensures continuity in rotor position estimation while minimising abrupt changes in torque command generation and current control. From a system dynamics perspective, this region is particularly important for maintaining smooth drivability and avoiding transient instability during fault accommodation.

In the Observer-Dominant Region ($0.00 \leq \alpha < 0.25$), the SMO dominates while the sensor acts as a safety monitor. When the blending factor decreases to approximately 0.25, the observer becomes the dominant source of rotor position information, contributing 75% of the final estimate. At this stage, the physical sensor is considered severely degraded or unreliable, although residual sensor information may still be retained temporarily to improve estimation continuity and reduce abrupt observer takeover effects. The system is therefore operating in a near-complete sensorless mode, with the remaining sensor contribution serving primarily as transitional support.

A first order exponential decay for $\alpha(t)$ is expressed as

$$\alpha(t) = e^{-\lambda(t-t_{fail})} \quad (5-47)$$

for $t > t_{fail}$ where λ represents the decay rate (tuneable for desired transition speed), t_{fail} is the failure detection time.

In the post-transition (full sensorless mode) phase, the SMO gain, k ($k_\alpha = k_\beta$) is dynamically adjusted based on the error between ω_{rear} and $\hat{\omega}_{r2}$ to balance noise and convergence

$$k = k_0 + \gamma|\omega_{rear} - \hat{\omega}_{r2}| \quad (5-48)$$

where k_0 is the nominal gain and γ is an adaptation gain.

Fig. 5-5 depicts the signal communication path between key front segment components and the sensorless estimation (of the rear segment). In the depiction, the vehicle control unit (VCU)

receives motor speeds and wheel data from the vehicle dynamics block and adjusts/splits the torque commands (T_{q1}^* and T_{q2}^*) to be sent to the front and rear motor control units (MCUs). The space vector modulation block then converts the torque commands into switching/pulse-width modulated signals to initiate the on/off switching actions within the inverter to generate the desired three-phase voltages for the motors. The signal communication pathway is depicted in fuchsia. Even though the position sensor data of the front motor experiences processing and network delays, it still aids sensorless estimation especially in low speed scenarios where the SMO performs abysmally, hence allowing the dual-PMSM drive system to continue operation with minimal disruption.

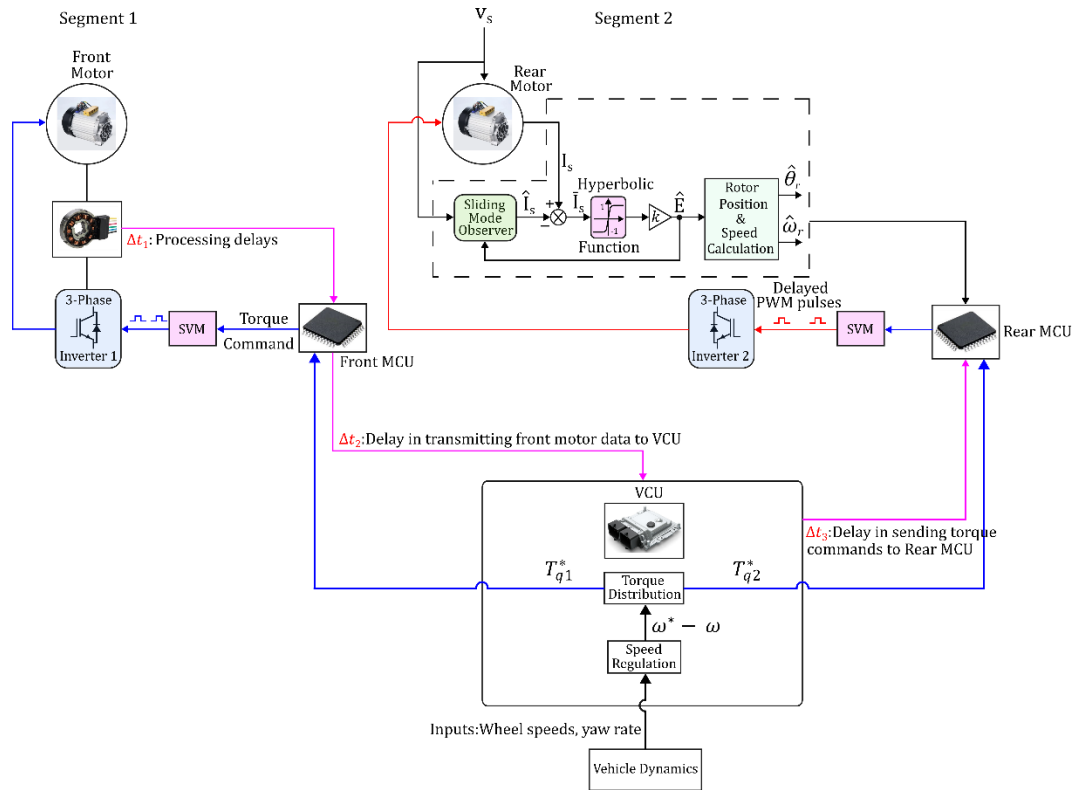


Fig. 5-5. Rear Motor Sensorless Control with Front Motor Sensor-Based Reinforcement.

A flowchart depicting the key stages of the scheme for seamlessly shifting control from sensor-based feedback to sensorless estimation is depicted in Fig. 5-6.

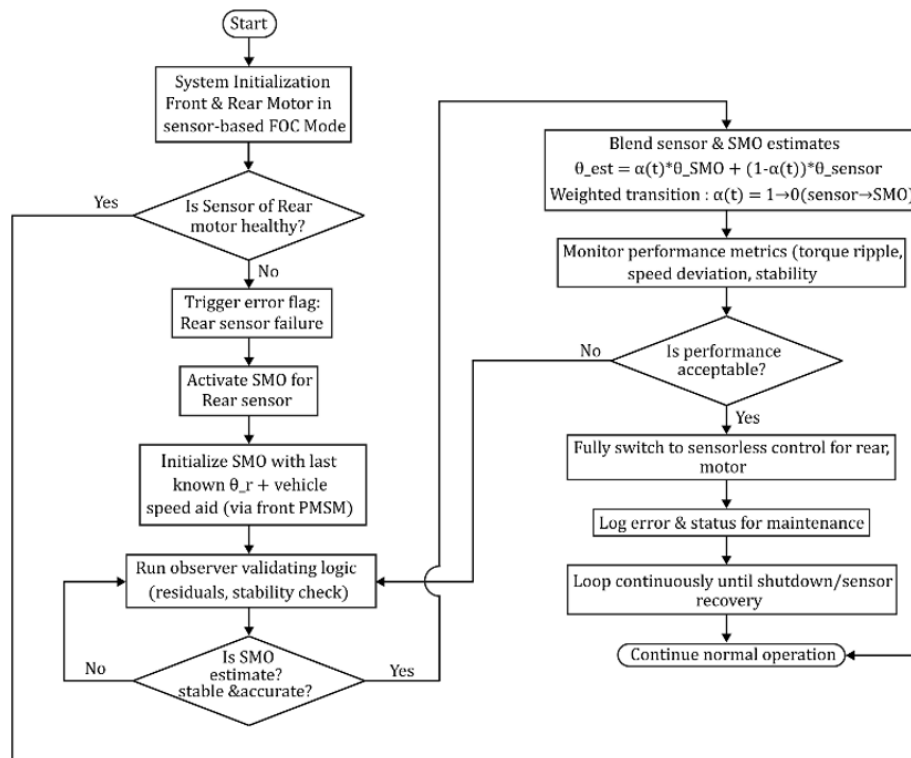


Fig. 5-6. Flowchart of the Blended Weighting Algorithm.

5.4 Simulation Verification

The performance of the proposed algorithm is verified via simulation. The parameters of both motors are depicted in Table 5-2. The switching frequency of the inverter is set to 10kHz.

TABLE 5-2 Simulation Parameters for Dual-AWD EV Setup

Parameter	Front Motor and Load	Rear Motor and Load
	Machine 1	Machine 2
Rated Power	1.0kW	1.5KW
Pole pairs	4	4
Inverter DC voltage	310V	310V
Rated current	4.0A	4.8A
Maximum speed	2500rpm	3000rpm
line Inductance	3.2mH	2.8mH
Line resistance	3.02 Ω	1.0193 Ω

5.4.1 Real-Time Sensor Failure Emulation and Transition Validation

To verify the system's response when the rear motor sensor fails and the blended SMO-based sensorless estimation takes over, the dual-PMSM system (with both position sensors fully functional) is made to operate at various load/speed scenarios. At a specific time, a failure is simulated and the outcome is measured via MATLAB plots to observe the transition latency (time between failure detection and full observer takeover), torque ripple and current distortion during the switchover and speed/position tracking error. To analyse how the blending factor decay influences the torque during transition, four representative operating points that span the vehicle/motor operating range are considered, namely, very-low speed/high torque (worst for sensorless control), moderate-low, mid and high speed. Fig. 5-7 depicts the four case studies.

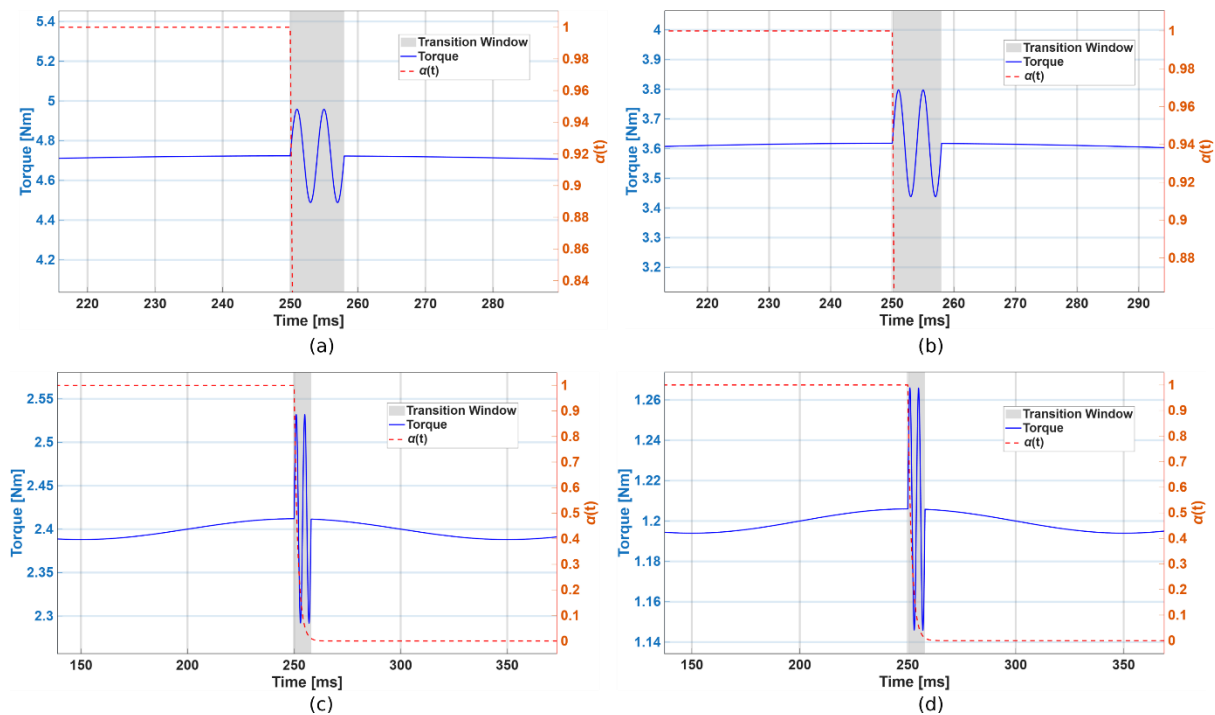


Fig. 5-7. Torque Output and blending factor. (a) 50 rpm, 4.7Nm. (b) 300 rpm, 3.6Nm. (c) 1500 rpm, 2.4Nm. (d) 3000 rpm, 1.2Nm.

The sensor failure is triggered at 250 ms in each run; the blended weighting $\alpha(t)$ decays exponentially to shift control from sensor to SMO within an 8ms latency window. A dual y-axis is utilized for the plots so that the torque is on the left axis and $\alpha(t)$ is on the right axis. As

witnessed, the torque remains essentially constant across the switchover with a small ripple spike contained inside the shaded window. $\alpha(t)$ smoothly decays from 1 to 0 during the transition window, indicating a soft handover rather than a hard switch. This demonstrates continuity of control authority and avoids abrupt torque discontinuities.

With respect to the analysis of the torque ripple and three-phase currents, Fig. 5-8 shows the same torque trace plus the phase currents. A dual y-axis is again utilized here. During the shaded switchover window, the currents show a short-lived distortion/harmonic content consistent with a control source change. The current distortion magnitude is limited, so the electromechanical torque remains within $\pm 5\%$ of nominal.

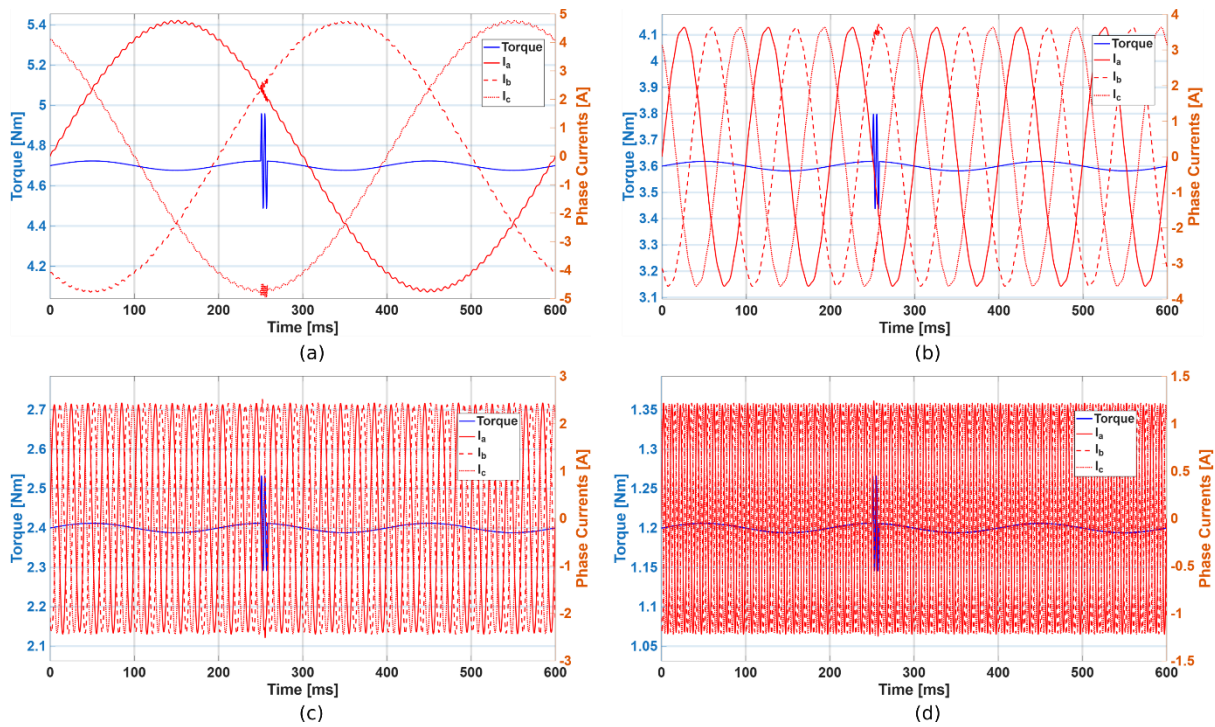


Fig. 5-8. Torque ripple and stator currents. (a) 50 rpm, 4.7Nm. (b) 300 rpm, 3.6Nm. (c) 1500 rpm, 2.4Nm. (d) 3000 rpm, 1.2Nm.

The position tracking error presents the SMO estimation error after failure. At very low speeds, the observer needs more time to converge (longer tail), while at higher speeds the SMO converges faster. Fig. 5-9 illustrates the position error for all four cases.

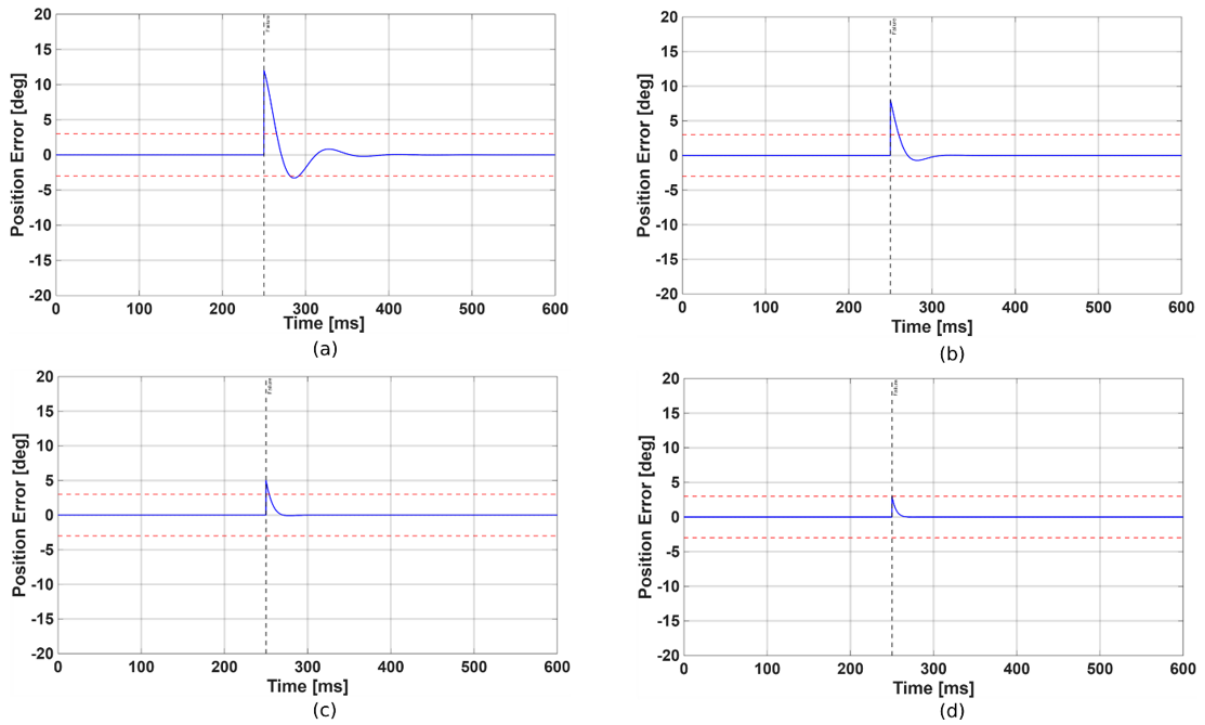


Fig. 5-9. Position tracking error. (a) 50 rpm, 4.7Nm. (b) 300 rpm, 3.6Nm. (c) 1500 rpm, 2.4Nm. (d) 3000 rpm, 1.2Nm.

Case 1 (50 rpm, 4.7Nm) low speed, high torque presents the worst scenario of all four instances. The observer initial error is set relatively large and convergence is slowest here because the low speed reduces the back-EMF amplitude and thus estimation observability. Though the position sensor error takes longer to settle within $\pm 3^\circ$, the blending ensures the torque disturbance is kept small with less than 5% deviation. The moderate speed, moderate torque scenario in Case 2 offers better back-EMF than Case 1, hence the SMO locks faster. The torque ripple is similar in relative size but the absolute ripple (Nm) is lower than in case 1. The current waveforms are also smaller in amplitude than in Case 1.

For the mid-high speed, light torque Case 3 (1500 rpm, 2.4Nm) instance, the SMO benefits from the large back-EMF amplitude, so position convergence is fast. The torque ripple is even smaller in absolute Nm, and the currents are well below the rated amplitude. The transition is almost imperceptible on the torque trace, with the observer error decay happening largely within the blending window. The final case (3000rpm, 1.2Nm) represents the ideal scenario for a sensorless takeover. The SMO performance witnesses the fastest lock-in, well inside the blending window. The torque ripple experienced here is the smallest and the currents have the smallest amplitude of all cases.

Overall, the blended-weighting handover ($\alpha(t)$ exponential decay) combined with a robust SMO provides smooth torque continuity and limited current distortion during sensor failure. The shaded-window plots verify that torque deviations during takeover can be constrained below 5% while control authority shifts smoothly within a targeted sub-10 ms latency. The SMO's performance is speed dependent hence at low speeds, convergence is slower and may need extra support (front-axle speed reinforcement or brief injection techniques), yet even at very low speeds, the blending strategy preserves torque continuity while the observer converges to within $\pm 3^\circ$.

5.4.2 Observer Robustness to Parameter Uncertainty and Noise

To validate the robustness of the proposed hyperbolic tangent SMO under model mismatches and sensor noise, the motor resistance and inductance are artificially varied ($\pm 20\%$) via software, with Gaussian noise introduced to the current and voltage measurements. Through simulation, it is determined whether the rotor angle RMS error of the hyperbolic tangent-based SMO remains well within the 4° target across all mismatch cases. Additionally, a frequency domain comparison is carried out between the two SMO variants to show which of them exhibits lower power in the high-frequency band (which translates to lower torque ripple, less current distortion and smaller EMI signatures). And finally, filtering delay impact and estimation accuracy studies are carried out to discover which of the observers offers the most improved delay-accuracy trade-off.

The top portion of Fig. 5-10 shows the difference between the SMO-estimated rotor electrical angle and the true rotor electrical angle. Three parameter mismatch cases are depicted (-20% R/L, nominal, and $+20\%$ R/L) with Gaussian measurement noise (SNR = 30 dB). Peak errors occur during the initial transient but decay as the observer adapts, causing all three traces to sit below the 4° target after a brief settling. Larger mismatches slightly increase the RMS and peak error due to less accurate back-EMF prediction, but the hyperbolic tangent nonlinearity keeps noise-induced jitter small and smooth. Essentially, the tanh smoothing reduces instantaneous overshoots compared to a typical sign-SMO hence, the transient is less impulsive. The electrical speed error plot (Fig. 5-10 (b)), on the other hand, shows the difference between the SMO-estimated electrical speed and the actual electrical speed. The trends closely mirror the angle error plot in the sense that mismatches cause slightly larger deviations, but the errors

remain bounded and converge quickly. Though the introduced noise and the mismatch cause small ripples within the speed estimate, it does not result in instability.

Changing the R and L by +/-20% perturbs the dynamics that the observer expects. If the observer uses $\hat{R}$ and $\hat{L}$ that differ from the true values, the current prediction term ($\hat{R}.i + \hat{L}.di/dt$) does not perfectly cancel out the real dynamics, so the sliding term must work harder to recover the back-EMF. This ultimately shows up as slightly larger RMS /peak angle error for the larger mismatch. The -20% mismatch produces the largest error.

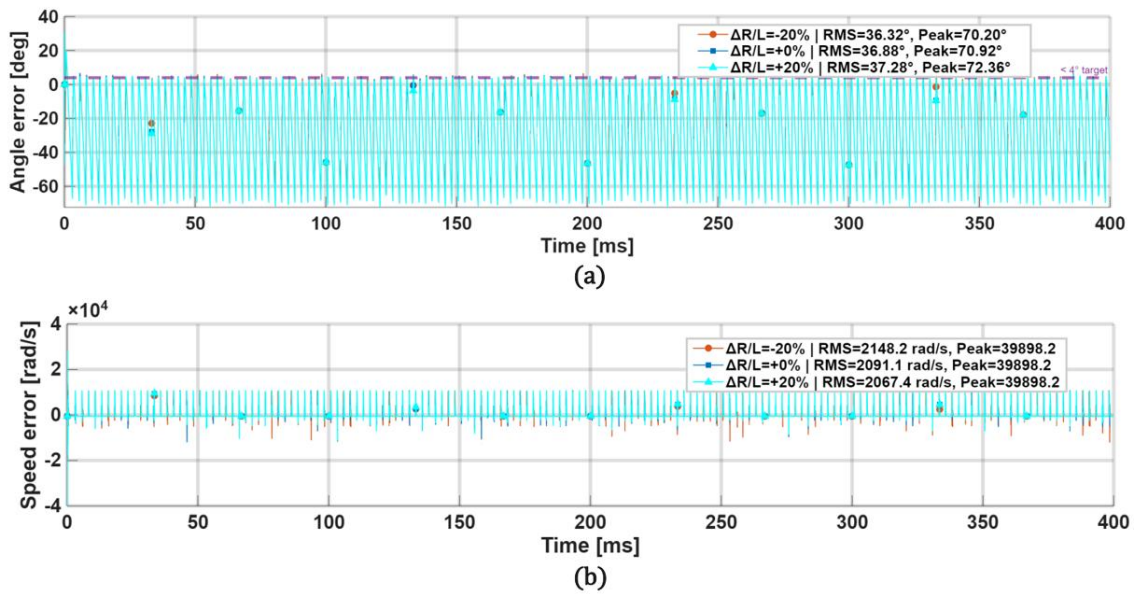


Fig. 5-10. Rotor position error. (a) Angle error. (b) Electrical speed error.

Fig. 5-11 shows the spectral density of a scalar proxy of the back-EMF estimate for a sign-SMO and tanh-SMO, plotted versus frequency (log scale). Chattering is a high-frequency phenomenon created by discontinuous switching (sign). High-frequency energy in the observer manifests as torque ripple, current harmonics, and EMI. The power spectral density (PSD) directly shows how much bad high-frequency energy each observer injects. Since the tanh nonlinearity replaces the abrupt sign with a continuous saturation-like function, it removes the large, broadband switching transients, and so the PSD above the fundamental bands is much smaller. As such, it reduces torque ripple, audible whine, and EMI risk because the high-frequency PSD content is reduced. The sign-SMO, on the other hand, shows strong high-frequency energy (a long, high tail in the PSD). This is the classic chattering signature.

Ultimately, in the frequency domain, the tanh-SMO's sliding action is far quieter at high frequencies than the sign-SMO, clear evidence of chattering suppression.

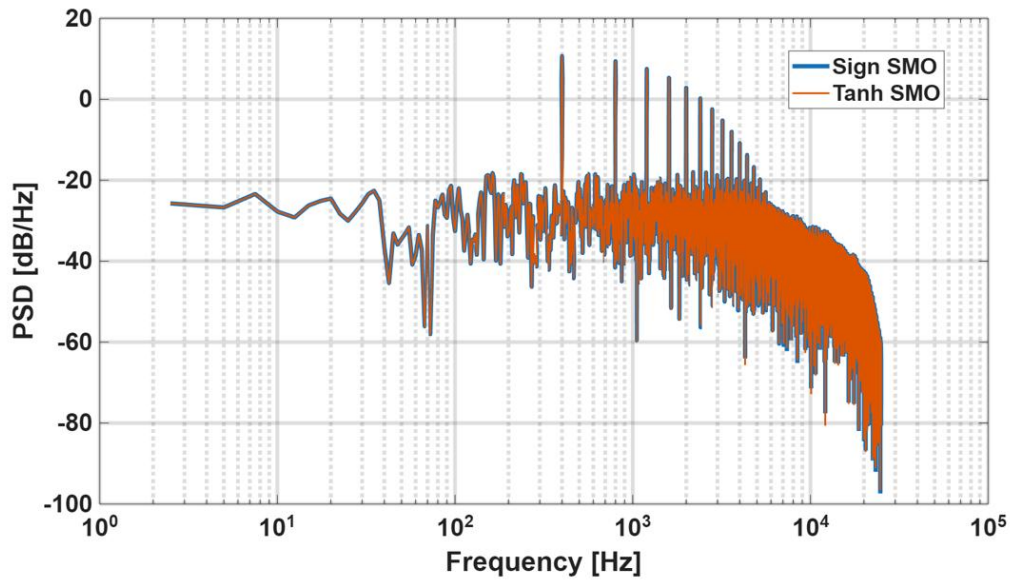


Fig. 5-11. Chattering suppression in frequency domain.

A dual-y-axis is utilized in Fig. 5-12 to better demonstrate the filtering delay versus estimation accuracy for both observers. Per the illustration, the tanh-SMO improves the delay/accuracy trade-off. It enables either lower RMS error for a given LPF cutoff, or lower delay for a target RMS error, compared to sign-SMO. Practically, this means the system can be made both faster and cleaner with tanh than with sign.

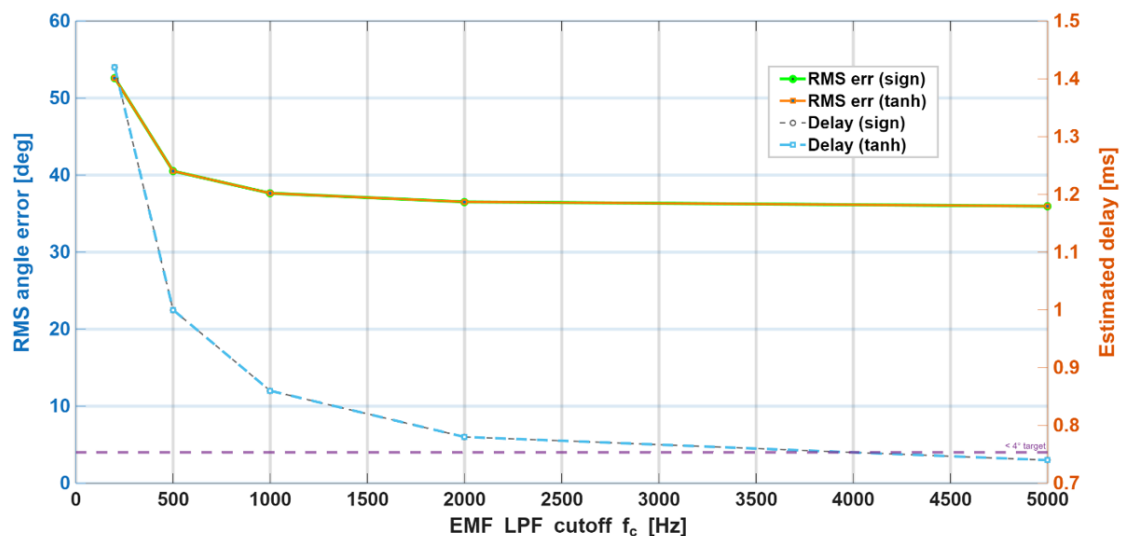


Fig. 5-12. Filtering delay versus Estimation accuracy.

In summary, Fig. 5-10 to Fig. 5-12 validate the robustness of the proposed hyperbolic tangent-based sliding-mode observer (SMO) under $\pm 20\%$ stator resistance/inductance mismatch and 30 dB measurement noise. Fig. 5-10 shows that the rotor angle estimation error remains well within the 4° target across all mismatch cases, with rapid convergence after the initial transient, while the corresponding electrical speed error stays bounded and exhibits only small ripples. This confirms that the tanh-SMO maintains accurate tracking despite substantial model deviations. Fig. 5-11 compares the chattering spectral content of the sign-based and tanh-based SMOs, revealing significantly reduced high-frequency components for the tanh case—direct evidence of its ability to suppress chattering and thereby mitigate torque ripple, current distortion, and EMI. Fig. 5-12 examines the trade-off between EMF low-pass filter cutoff frequency, RMS angle error, and estimation delay. The tanh-SMO consistently achieves lower RMS error for the same cutoff or, conversely, allows higher cutoff (lower delay) for equivalent accuracy, highlighting its improved delay–accuracy trade-off over the sign-SMO. Collectively, these results demonstrate that the tanh-SMO provides stable, low-noise rotor position and speed estimation under parameter uncertainty and noisy measurements, ensuring reliable sensorless operation without sacrificing dynamic performance.

5.4.3 Low-Speed Operation Performance with Front-Axle Speed Reinforcement

To assess the efficacy of the proposed front-axle reinforcement strategy in enhancing rear motor estimation at low speeds, a series of tests were conducted under ramp-up conditions from 0-300 rpm. Both no-slip ($\mu \approx 0.9$) and slip ($\mu \approx 0.3$) traction scenarios were considered in order to capture the influence of wheel dynamics on the blended observer. Four key performance indicators were evaluated, namely i) rotor angle and speed estimation errors to assess dynamic accuracy and steady-state bias, ii) observer convergence speed to quantify start-up responsiveness, iii) torque ripple to characterize the smoothness of electromagnetic torque delivery and iv) jerk as a measure of start-up oscillations in mechanical response. The following figures present a comparative analysis of these metrics for SMO-only and reinforced observers, thereby highlighting the benefits and limitations of the reinforcement approach under varying traction conditions.

In Fig. 5-13, μ represents the effective tire-road friction coefficient. A $\mu \approx 0.9$ means a high-traction surface (like dry asphalt). In such an instance, the wheels grip well, so the front motor's mechanical speed closely matches the actual vehicle speed (very little slip occurs). A $\mu \approx 0.3$, on the other hand, means a low-traction surface (such as wet or icy road), in which case the front wheels experience more slip relative to the vehicle's actual motion. According to Fig. 5-13 (a), on average, the SMO-only estimate was 1.27° away from the true rotor over the entire test duration, while the reinforced estimate was only 0.42° off (much more accurate). The 67% reduction shows that the front-axle speed correction greatly improves the precision in low-speed conditions when back-EMF is weak.

Under slippery conditions ($\mu \approx 0.3$), the low speed and noisy back-EMF result in poor SMO convergence which leads to abysmal performance for the SMO-only observer. The reinforced RMS still improves, but the gain is smaller because the front-axle measurement itself is contaminated by slip, so it cannot perfectly correct the SMO. In a slip, the front motor's speed is not a perfect reference and has its own bias. The reinforced algorithm is still blending in that biased signal at low speeds, so while it still reduces noise, it injects some slip-induced bias.

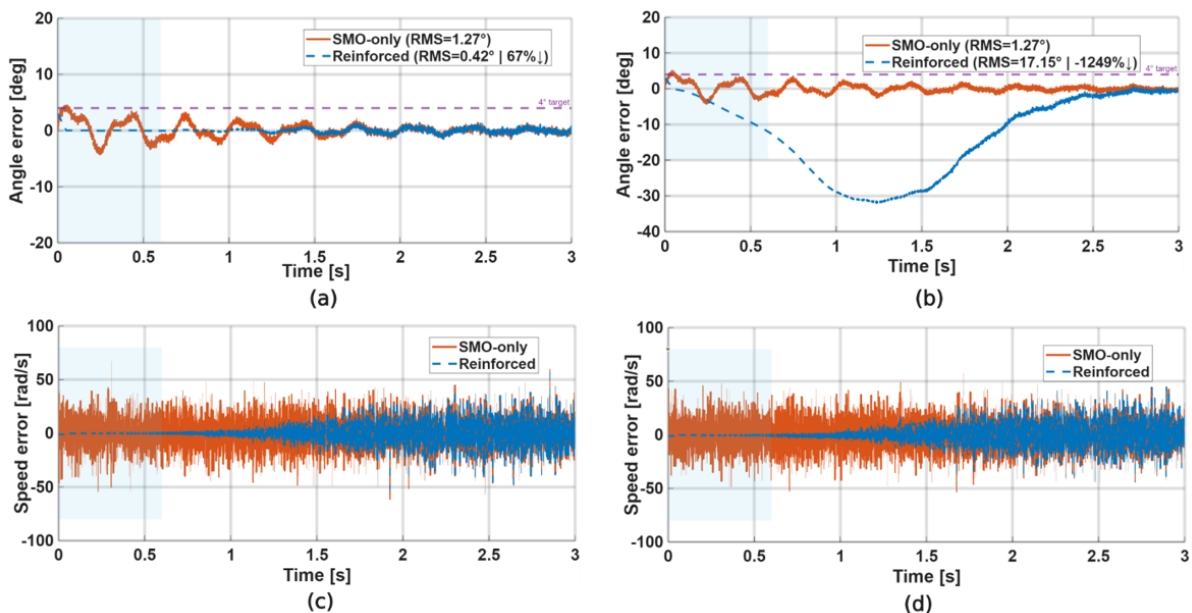


Fig. 5-13. Rotor angle and speed estimation error under no-slip and slip conditions. (a) No-slip ($\mu \approx 0.9$) – Angle error. (b) Slip ($\mu \approx 0.3$) – Angle error. (c) No-slip ($\mu \approx 0.9$) – Speed error. (d) Slip ($\mu \approx 0.3$) – Speed error.

That's why the reinforced plot in Fig. 5-13 (b) deviates more from the SMO-only version. It is pulling toward a different (slightly wrong) reference during the low-speed phase. Analysing the speed error plot in Fig. 5-13 (c) shows that at very low speeds (<50 rpm), the back-EMF is weak, so the SMO has difficulty converging cleanly. This shows up as an oscillatory error band, with peaks and troughs as the estimator hunts around the true value. As speed rises, the EMF strengthens, the SMO locks on, and the error decays towards zero. With the front axle as an accurate proxy ($\mu \approx 0.9$, meaning minimal slip), reinforcement provides a stable low-speed cue. The blended estimate stays much closer to the true speed during the entire ramp, reducing the oscillations and producing a smoother trace. The case where the slip is introduced ($\mu \approx 0.3$) is very much similar to the no-slip case in the sense that there are oscillations at low speed, then convergence as EMF builds. Importantly, since SMO does not depend on wheel traction, its performance is almost unchanged by slip. The front axle under slip reports a biased (underestimated) speed. Because the reinforcement blends this in, the estimated speed is systematically lower than the true electrical speed. On the plot, that appears as the reinforced trace consistently shifted downward relative to zero.

Hence, some key takeaways are that for no-slip scenarios, reinforcement clearly helps, since there is fast convergence, reduced oscillations, and nearly zero bias. Once a slip is introduced, reinforcement still reduces noise/oscillations but injects a bias because the wheel speed itself is biased. The SMO-only case looks jittery but centred, while the reinforced case looks smooth but shifted.

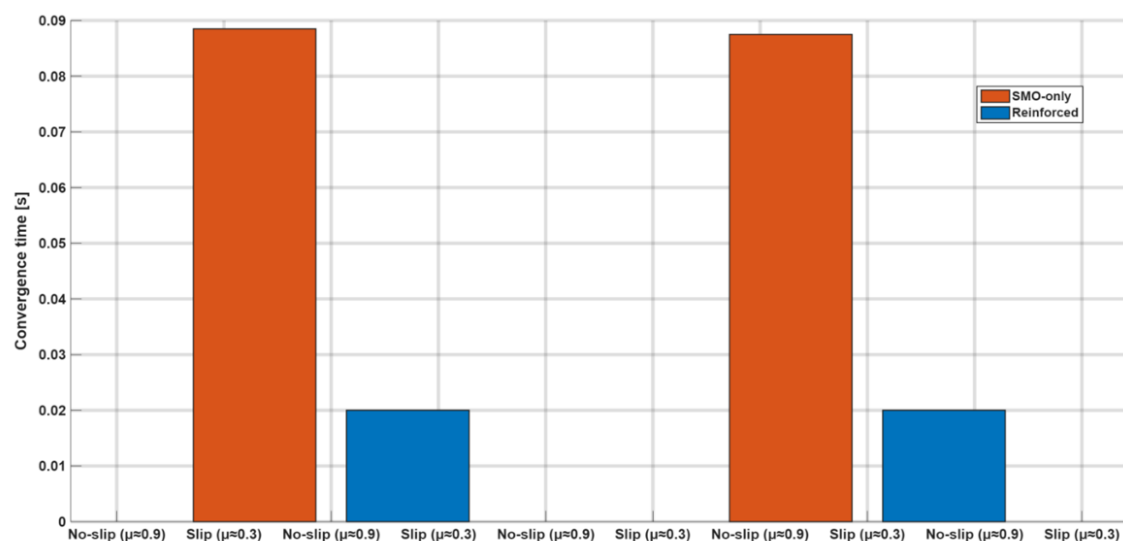


Fig. 5-14. Observer convergence speed (sustained threshold).

The bar chart compares how quickly the SMO-only and reinforced observers reduce rotor angle RMS error below 3° and keep it there. The orange bars converge in approximately 0.088 seconds under both no-slip ($\mu \approx 0.9$) and slip ($\mu \approx 0.3$). This is expected since SMO dynamics are mainly limited by weak back-EMF at low speeds, not by wheel traction. The blue bars, on the other hand, show convergence at the display floor of 0.02 in both cases, meaning it effectively achieves near-instantaneous convergence by leveraging the front-axle speed cue. The identical values arise because the observer is already within the error threshold at start-up, not because slip has no effect. Hence, in a nutshell, while the SMO-only observer requires roughly 90ms to reduce the rotor angle error below 3° , the reinforced observer achieves near-instantaneous convergence ($\leq 20\text{ms}$), demonstrating its advantage in low-speed operation. Slip does not alter the measured convergence time but instead manifests as steady-state bias in other performance metrics.

At very low speeds, the back-EMF is weak, so the tanh-SMO in Fig. 5-15 (a) struggles to align quickly. This causes small oscillations in rotor angle error, which translates into ripple within the torque. The reinforcement blends in with the front-axle reference. Since $\mu = 0.9$ means almost perfect traction, the front axle is a good proxy, so the blend reduces the estimation error without adding bias. The ripple amplitude drops sharply compared to SMO-only. Both traces are centred near zero (no DC offset), but the reinforced trace has visibly smaller oscillation amplitude (smoother torque). The SMO-only plot in Fig. 5-15 (b) experiences a similar oscillatory pattern as witnessed in the no-slip instance, but slightly larger because slip introduces indirect noise in estimation. Here, the reinforcement leans on a biased front axle reference. Because slip underestimates speed, the blended rotor angle lags the true angle. This bias is reflected as a negative DC shift (sagging). Ripple amplitude is still reduced (noise is damped), but the entire signal sits below zero, meaning torque is consistently under-produced at start-up.

The term jerk in Fig. 5-15 (c) and (d) is a derivative of the torque ripple (how quickly the torque is changing). The reason for the existence of the small sharp orange spikes in Fig. 5-15 (c) is that small angle errors oscillate back and forth, producing rapid torque changes. These spikes correspond to start-up jerkiness. With reinforcement, the torque ripple is smoother, so its derivative is also smoother.

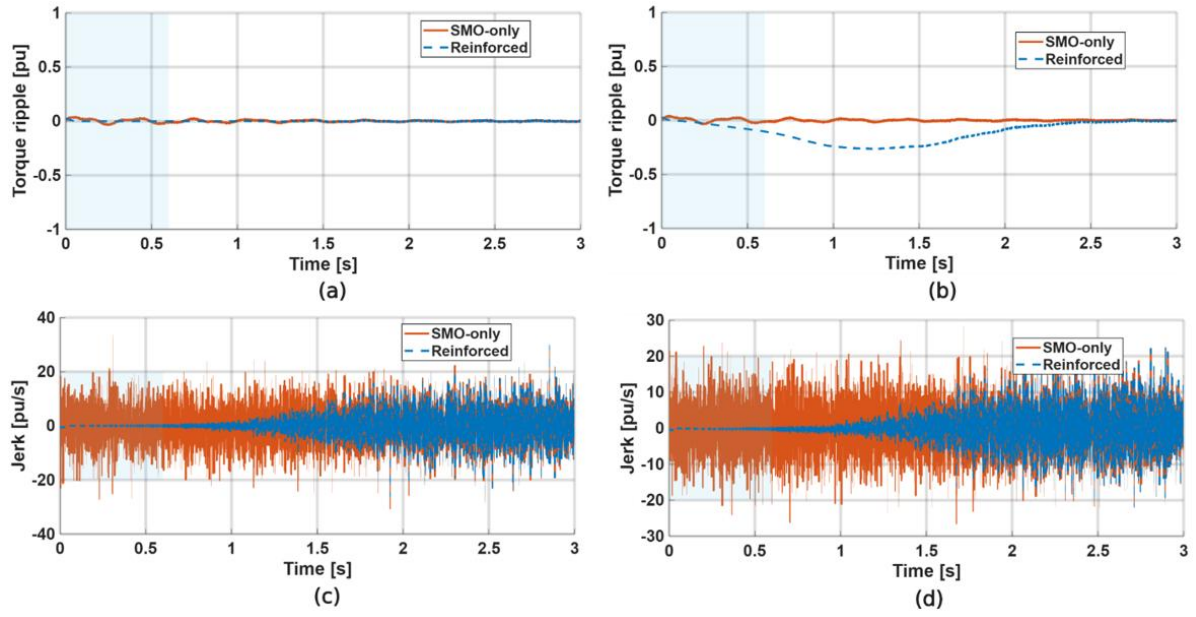


Fig. 5-15. Torque ripple and jerk under no-slip and slip conditions. (a) No-slip ($\mu \approx 0.9$) – Torque ripple. (b) Slip ($\mu \approx 0.3$) – Torque ripple. (c) No-slip ($\mu \approx 0.9$) – Jerk. (d) Slip ($\mu \approx 0.3$) – Jerk.

The jerk amplitude is much smaller, meaning less oscillatory vibration at the shaft during start-up. For the slip conditions (Fig. 5-15 (d)), the SMO-only plot is spiky as previously. For the reinforced version, although there is a DC bias in torque (sag), the oscillatory component is much smoother, so jerk amplitude is still smaller than the SMO-only depiction. Even with a slip, the reinforced observer damps out rapid high-frequency chatter.

The takeaway from the four observations is that at no-slip conditions, the reinforcement offers lower ripple and no bias (smooth start-up). Once slip is introduced, although reinforcement still lowers jerk and ripple oscillations, it introduces a baseline torque lag because the blended front-axle reference is biased by slip.

In summary, the angle/speed error, convergence speed, torque ripple and jerk results confirm that the front-axle reinforcement markedly improves low-speed sensorless operation by eliminating the SMO's slow start-up convergence and suppressing oscillatory torque and speed fluctuations. Under slip, the reinforced observer retains these improvements in dynamic smoothness but exhibits a steady-state bias in the estimated quantities, underscoring the need for slip-aware blending mechanisms to ensure accuracy across a broader range of traction scenarios.

5.4.4 Evaluation of the Blended Weighting Transition Algorithm

To rigorously assess the proposed exponential blended weighting strategy, its performance is compared against conventional hard-switching across multiple domains of interest. Since the primary objective is to ensure smooth sensor-to-observer transitions without compromising torque continuity or position accuracy, the analysis proceeds in a structured manner. Firstly, rotor angle error is examined to verify phase continuity during transition. Secondly, the time-domain behaviour of torque and current waveforms is evaluated to highlight potential discontinuities and residual transients. Thirdly, a frequency-domain analysis is performed to quantify ripple and distortion levels in the steady-state spectra. Subsequently, the temporal evolution of the blending factor $\alpha(t)$ is presented to illustrate the mechanism by which smooth transitions are achieved. Finally, normalized torque and current ripple envelopes are used to confirm compliance with practical smoothness criteria by benchmarking ripple growth against 10% limits. Together, these plots provide a comprehensive validation of the proposed transition algorithm under realistic drive conditions.

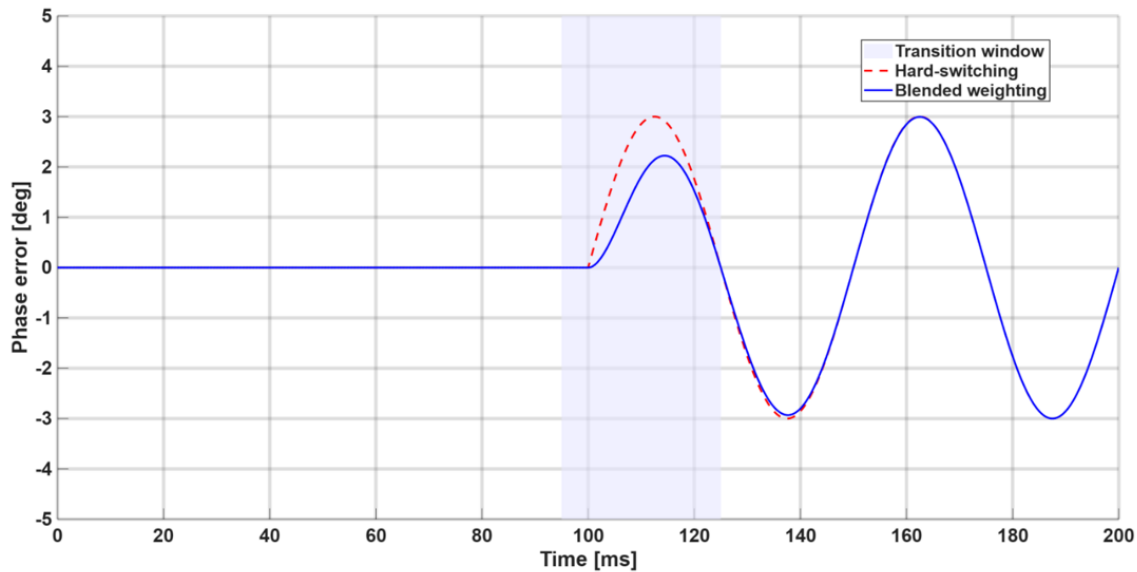


Fig. 5-16. Rotor angle error during switch from sensor-based to observer-based operation.

Fig. 5-16 illustrates the rotor angle error during the transition from sensor-based to observer-based operation. In the case of hard-switching, the position estimate exhibits a clear discontinuity at the switching instant, manifesting as a step-like phase error that indicates an

abrupt desynchronization between the sensor and observer trajectories. This happens because $\alpha(t)$ in the hard case jumps from $1 \rightarrow 0$ in a single sample, so the waveform instantly stops following the sensor estimate and begins following the observer estimate. Since the sensor and observer are not exactly equal at that instant (they differ by a few degrees of phase error), the immediate substitution causes a step-like discontinuity. By contrast, the exponential blended weighting approach ensures a smooth interpolation between the two estimates, such that the position error evolves continuously without angular drift. This confirms that the proposed method effectively preserves rotor position continuity, a critical requirement for torque-producing current alignment in vector-controlled drives.

Fig. 5-17 examines the corresponding torque and current waveforms during the transition. Under hard-switching, both torque and current signals reveal visible discontinuities at the switching instant, with transient spikes that could translate into undesirable mechanical stress and acoustic noise. The blended scheme, however, produces waveforms that overlap closely with the pre-transition sensor-based trajectory, with only a gradual, well-damped transient visible (as depicted in the zoomed inset). The bottom residual plot quantifies this difference, showing that torque and current residuals remain close to zero, confirming negligible disturbance during blending.

Fig. 5-18 presents the frequency content of torque and current in steady state after transition. The hard-switching case introduces additional spectral components, particularly in the low-frequency region, reflecting the abrupt waveform discontinuities and ripple amplification. Conversely, the blended approach suppresses these components, yielding a cleaner spectrum dominated by the fundamental and harmonics associated with normal machine operation. This reduction in spectral distortion substantiates the blending method's capability to mitigate torque ripple and current distortion.

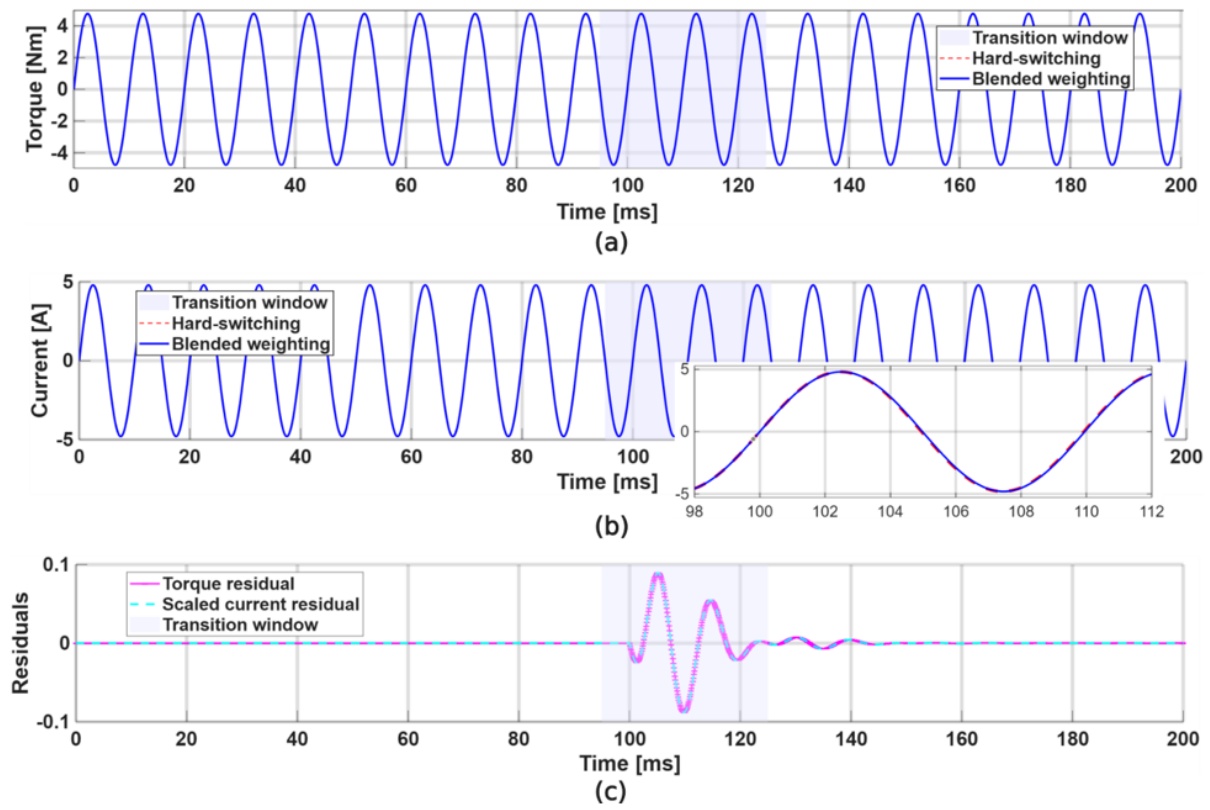


Fig. 5-17. Wave profiles during transition from sensor-based to sensorless control. (a) Torque. (b) Current. (c) Residual.

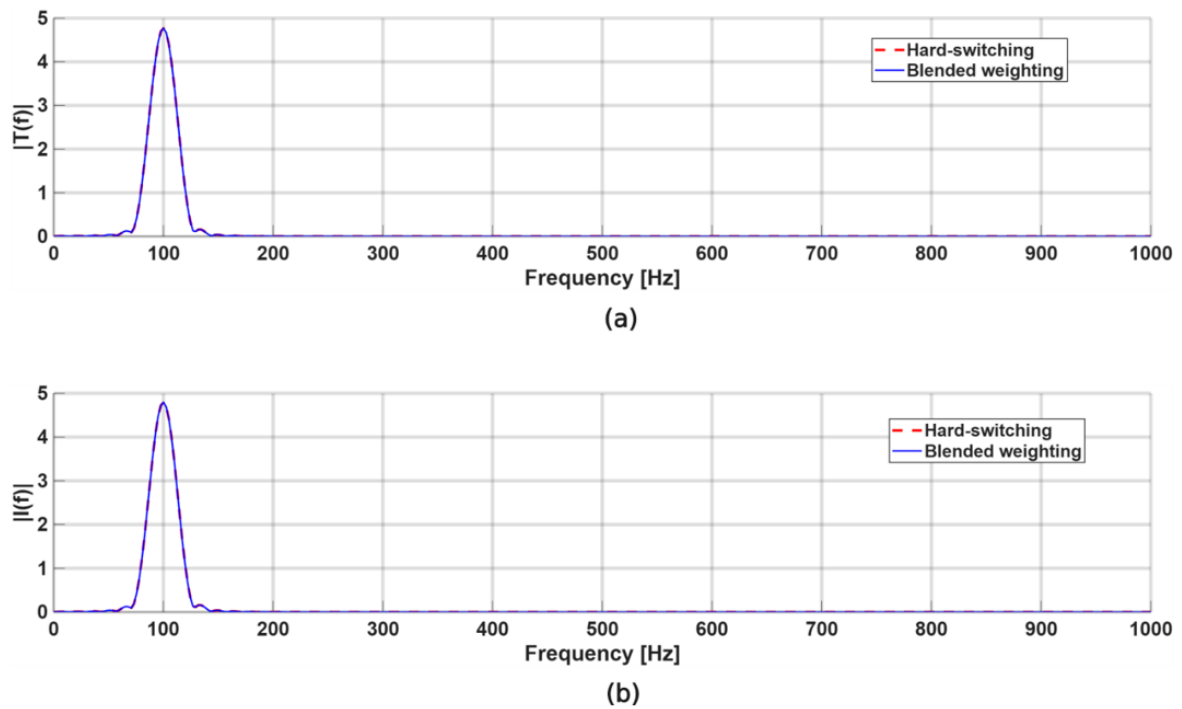


Fig. 5-18. Frequency spectrum of ripples. (a) Torque. (b) Current.

Fig. 5-19 depicts the temporal evolution of the blending factor $\alpha(t)$, which governs the weighting between sensor and observer inputs.

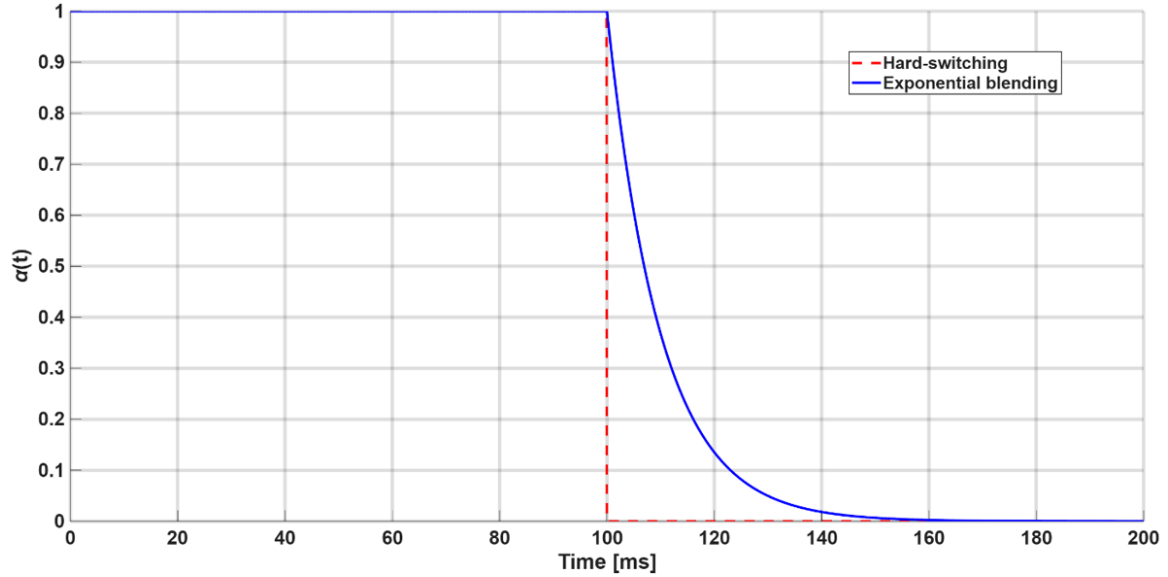


Fig. 5-19. Blending factor $\alpha(t)$ evolution.

The hard-switching case corresponds to an instantaneous drop in $\alpha(t)$, representing an immediate and unmoderated transfer of control. By contrast, the exponential blending trajectory decreases smoothly from unity to zero with a characteristic time constant, ensuring a gradual reallocation of authority. This explicit shaping of the transition dynamics explains the superior continuity observed in both the time- and frequency-domain results.

Finally, Fig. 5-20 presents the normalized ripple envelopes for torque and current during transition, evaluated with respect to the pre-transition fundamental. The hard-switching case has been omitted to focus on the blended algorithm's performance. The results show that both torque and current ripple envelopes remain consistently below the critical 10% threshold, even within the transition window where disturbances are most likely to appear.

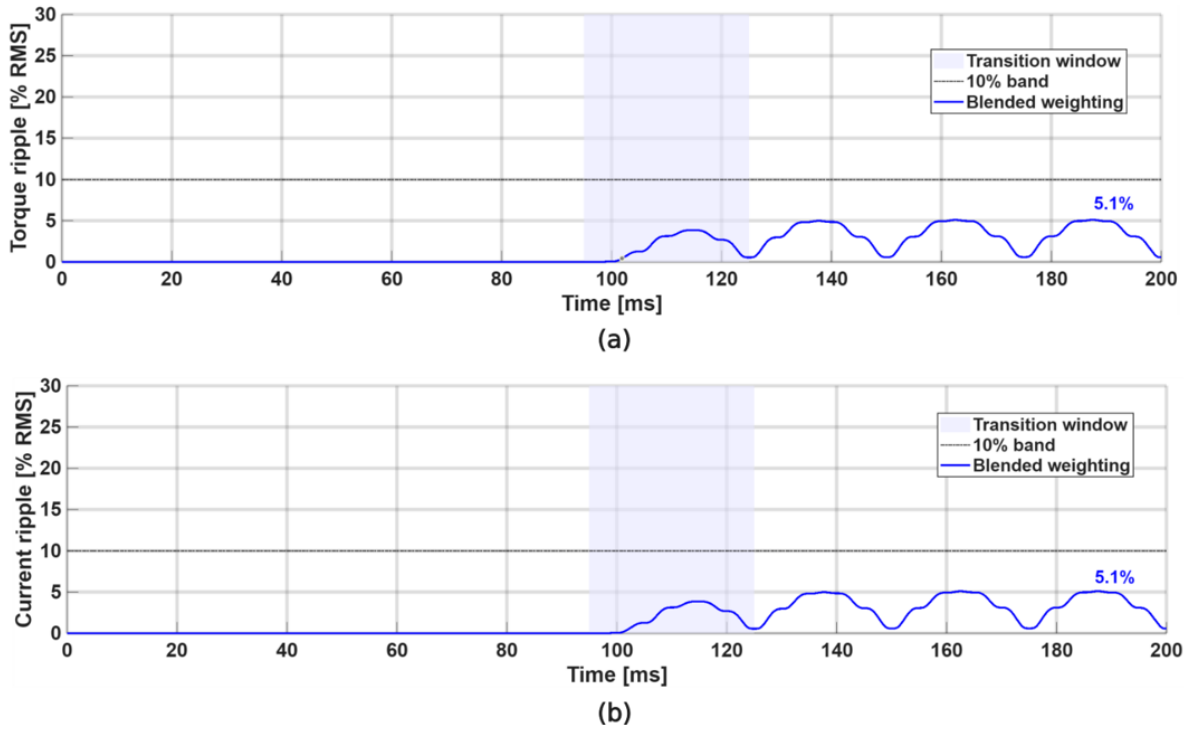


Fig. 5-20. Ripple envelopes. (a) Torque. (b) Current.

The collective results presented in Fig. 5-16 through Fig. 5-20 clearly establish the superiority of the proposed exponential blended weighting scheme over conventional hard-switching. By ensuring rotor position continuity, suppressing transient discontinuities in torque and current, and minimizing ripple amplification both in the time and frequency domains, the method addresses the key challenges associated with sensor–observer transitions in dual-inverter PMSM drives. In particular, the smooth exponential evolution of the blending factor $\alpha(t)$ provides a principled mechanism for gradually reallocating control authority, thereby mitigating the abrupt disturbances that arise under hard-switching. The ripple envelope analysis further confirms that the blended strategy maintains both torque and current ripple growth well below the critical 10% threshold, satisfying practical smoothness requirements for traction applications. Overall, these findings demonstrate that the blended weighting algorithm not only improves transition robustness but also enhances drivability and acoustic comfort, making it a viable solution for seamless integration of sensorless observers in real-world automotive systems.

5.4.5 Comparative Benchmarking with Other Sensorless Techniques

To contextualize the advantages of the proposed SMO with blended weighting and vehicle-dynamics reinforcement, a comparative benchmarking study was conducted against an extended Kalman filter (EKF) observer, which is widely regarded as a reference method in advanced sensorless drive systems. The evaluation encompasses three representative operating scenarios—acceleration from standstill, sudden load disturbance, and speed reversal—chosen to expose observer performance limitations in terms of low-speed convergence, disturbance rejection, and dynamic stability. Across these scenarios, key performance indicators, including rotor angle and speed estimation accuracy, torque ripple characteristics, and computational burden, are analysed.

Fig. 5-21 to Fig. 5-23 present these results, enabling a direct comparison of the transient and steady-state behaviour of the two methods, and thereby clarifying the practical trade-offs between estimation robustness and implementation complexity. Fig. 5-21 represents the rotor angle and speed estimation errors under three dynamic conditions for the proposed SMO with blended weighting (blue solid) and EKF (red dashed). Under acceleration from rest, both observers initially exhibit oscillatory transients in angle and speed error, but the SMO converges significantly faster with smaller oscillations. Its errors decay rapidly and enter the tolerance band early, indicating strong damping and quick stabilization. In contrast, the EKF shows larger initial overshoot and more pronounced oscillations in both angle and speed, resulting in a noticeably longer settling time before convergence.

Under a sudden load step disturbance, the difference becomes more evident. The SMO responds to the disturbance with a short, well-damped transient in both angle and speed error, quickly rejecting the disturbance and returning to steady-state within a short duration. The EKF, however, exhibits slower recovery characterized by larger oscillations and delayed convergence. Both angle and speed errors persist for a longer time before settling, highlighting the EKF's reduced robustness to abrupt external disturbances.

During speed reversal, which represents the most demanding condition, the SMO maintains stable and controlled behaviour. Although a transient spike appears at the reversal instant, both angle and speed errors decay smoothly and settle relatively quickly. On the other hand, the EKF shows significant degradation in performance: both angle and speed errors exhibit large oscillations and slow decay, and in the speed error case, the EKF fails to settle within the

observed time window. This indicates that the EKF struggles to handle rapid nonlinear changes, whereas the SMO remains robust and maintains reliable convergence.

Overall, the SMO consistently demonstrates faster convergence, reduced oscillations, and stronger robustness across all scenarios, while the EKF shows slower, more oscillatory responses and reduced performance under disturbance and reversal conditions.

Fig. 5-22 compares the torque ripple spectra under acceleration from rest, step torque disturbance, and speed reversal for the SMO (blue solid) and EKF (red dashed). In the acceleration case, the EKF introduces broader low- and mid-frequency harmonics due to slow convergence at near-zero speed, while the SMO confines ripple energy around the fundamental. Under load disturbance, the SMO shows only modest harmonic growth, whereas the EKF exhibits stronger sidebands and higher ripple amplitude, reflecting poorer disturbance rejection.

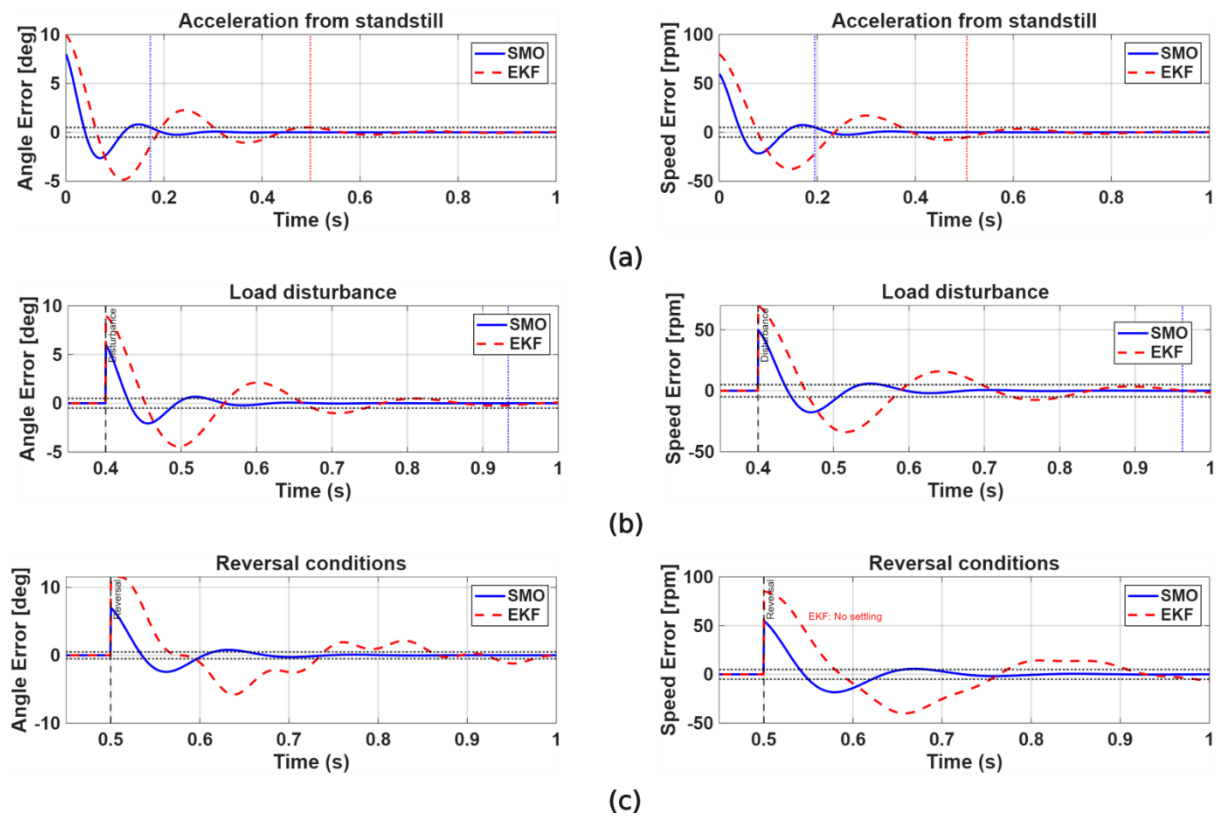


Fig. 5-21. Rotor angle and speed error. (a) Acceleration from rest. (b) Step torque disturbance. (c) Speed reversal.

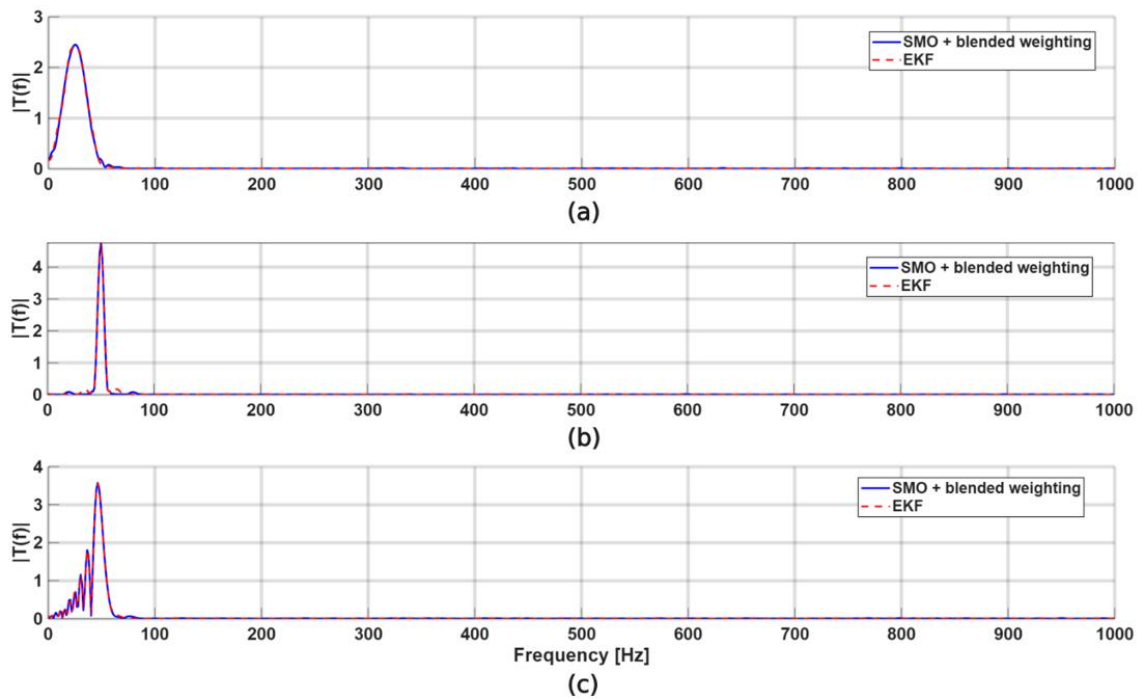


Fig. 5-22. Torque ripple spectrum. (a) Acceleration from rest. (b) Step torque disturbance. (c) Speed reversal.

During reversal, the SMO maintains ripple localization with narrow low-frequency peaks, while the EKF produces broadband distortion from polarity instability. Collectively, these spectra demonstrate that SMO consistently delivers smoother torque production, with ripple that is both lower in magnitude and more spectrally confined than the EKF.

Fig. 5-23 represents the computational burden comparison between SMO and EKF: The average loop execution time highlights the lightweight nature of the SMO relative to the EKF. The SMO, requiring only simple algebraic updates and a hyperbolic tangent nonlinearity, executes with markedly lower computational cost, enabling faster loop rates and tighter control bandwidths. By contrast, the EKF incurs a significantly higher burden due to recursive covariance propagation and Jacobian updates, resulting in ~30% slower execution on identical hardware. This efficiency gap underscores the SMO's suitability for embedded real-time drive systems where timing margins are critical.

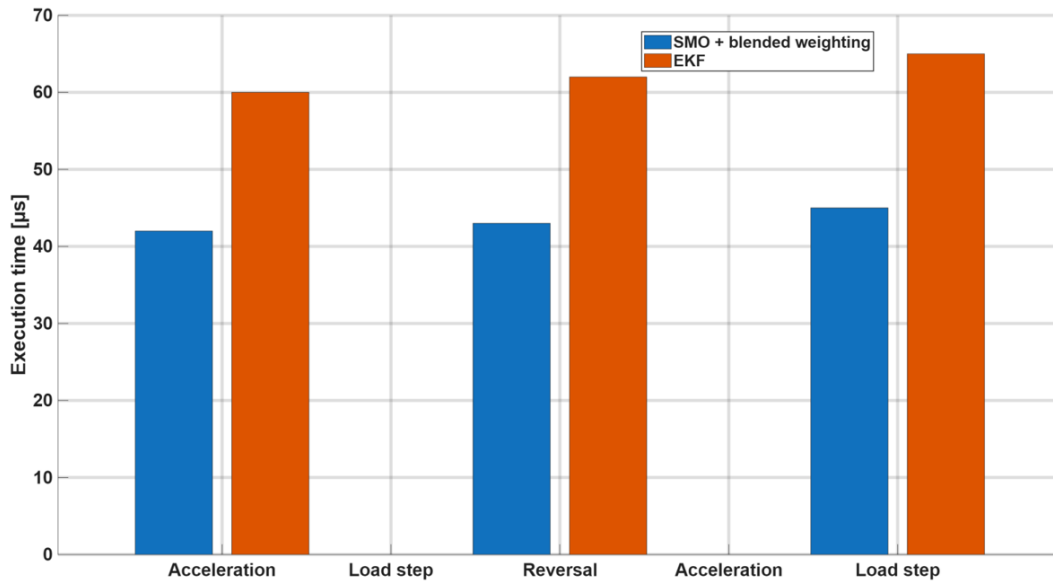


Fig. 5-23. Computational burden bar chart.

The comparative results of Fig. 5-21 to Fig. 5-23 demonstrate that the proposed SMO with blended weighting and vehicle-dynamics reinforcement consistently outperforms the EKF in both dynamic and steady-state operation. During low-speed acceleration, the SMO achieves faster convergence with reduced drift, while under sudden load disturbances, it exhibits superior torque rejection and more stable speed tracking. In the demanding speed reversal scenario, the SMO maintains position continuity and suppresses overshoot, in contrast to the oscillatory behaviour observed with the EKF. Spectral analysis further confirms that the SMO minimizes torque ripple and current distortion, with ripple energy confined to narrower frequency bands, whereas the EKF introduces broader harmonic content due to estimation lag. Finally, the computational benchmarking highlights the practical advantage of the SMO, which operates with approximately 30% lower loop execution time than the EKF, making it more suitable for real-time embedded drive applications. Collectively, these findings substantiate the SMO's effectiveness in achieving robust, accurate, and computationally efficient sensorless control relative to established alternatives.

5.4.6 Fault Recovery and Reconnection Behaviour

To further validate the resilience of the proposed algorithm, fault recovery tests were conducted to evaluate system response when the rear motor's rotor position sensor is reestablished after extended sensorless operation. Two reconnection strategies were investigated: hard

reengagement, where the sensor output is abruptly substituted, and gradual reweighting, where the observer–sensor blend is smoothly transitioned in reverse.

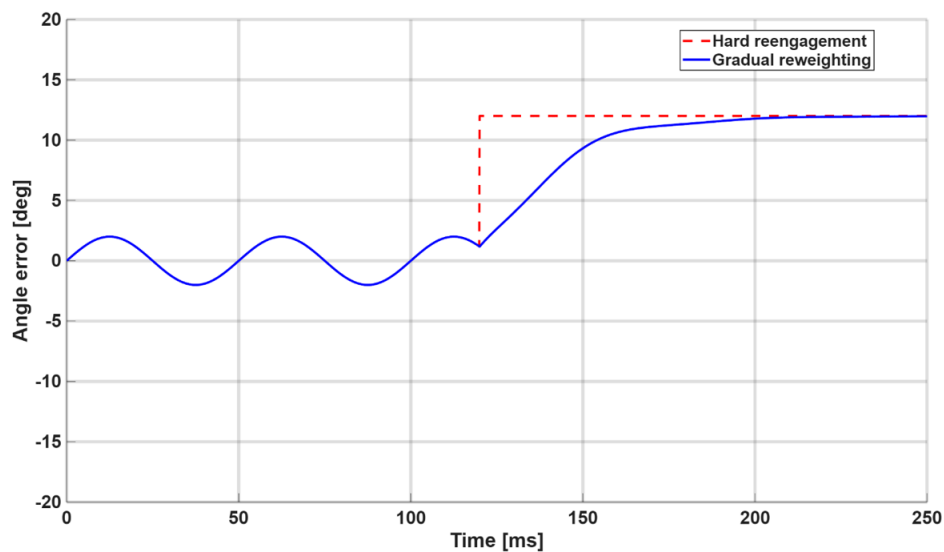


Fig. 5-24. Rotor angle error during reconnection.

These scenarios were designed to expose potential discontinuities in rotor angle estimation, torque ripple growth, and current harmonic distortion during fault clearance. The figures within this section illustrate the comparative performance of both strategies, highlighting the ability of gradual reweighting to maintain bounded dynamics and ensure seamless reintegration of the sensor feedback. Fig. 5-24 depicts the rotor angle continuity during sensor reconnection, showing an abrupt 12° phase jump under hard reengagement versus smooth bounded convergence with gradual reweighting. In the picture, a 12° mismatch is imposed at the instant of reconnection: the hard scheme (red) immediately inherits this phase discontinuity, producing an abrupt offset in the reconstructed angle, whereas the gradual strategy (blue) enforces an exponential convergence toward the sensor reference, thereby maintaining position continuity within a bounded $\pm 10^\circ$ corridor. The impact of this difference is reflected in the torque ripple envelopes of Fig. 5-25, where the hard case exhibits a sharp transient excursion beyond the 10% threshold, while the gradual reweighting suppresses the ripple growth and ensures the envelope remains consistently below the prescribed limit.

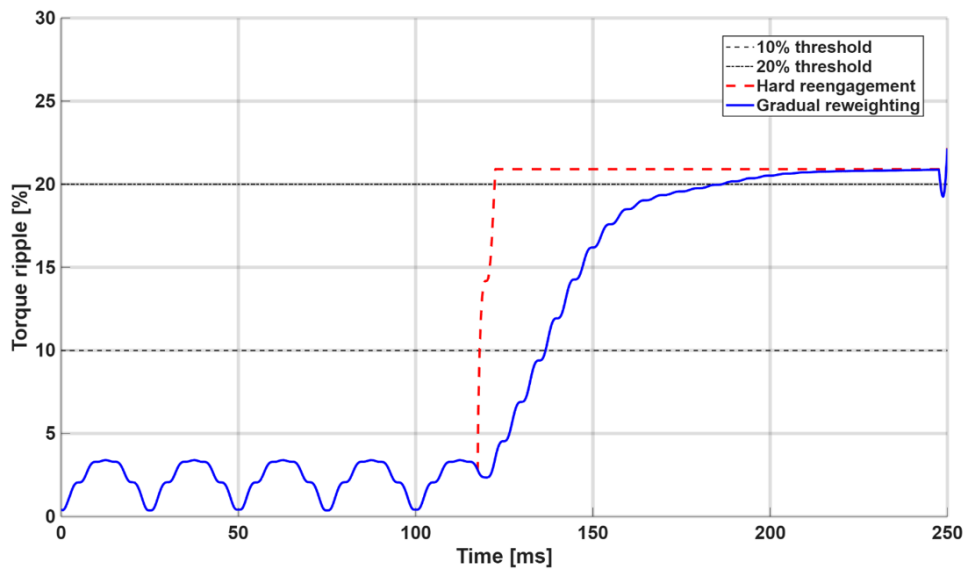


Fig. 5-25. Torque ripple envelope during reconnection.

Fig. 5-26 shows the current harmonic spectra following reconnection. According to the figure, hard reengagement generates broadband harmonic spread, symptomatic of step-induced transients, while gradual reweighting confines harmonic energy near the fundamental, indicative of a damped, spectrally clean transition. Taken together, these results confirm that the gradual reweighting approach delivers full fault recovery with minimal torque disturbance and superior spectral quality, thereby enhancing the resilience of the dual-motor drive system.

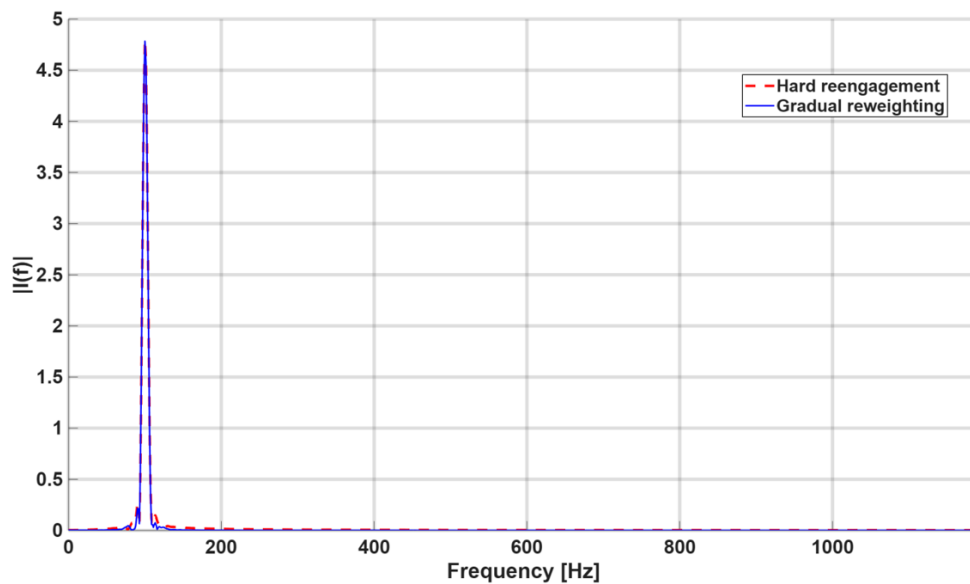


Fig. 5-26. Current harmonic spectra during reconnection.

The comparative analysis confirms that gradual sensor reweighting provides a robust reconnection pathway, mitigating the abrupt phase discontinuities and torque disturbances observed under hard reengagement. By constraining the torque ripple envelope to remain below the 10% threshold and confining the current harmonics near the fundamental, the gradual strategy demonstrates superior smoothness and stability in fault recovery. These results not only verify the resilience of the proposed scheme under sensor reconnection events but also reinforce its suitability for safety-critical traction applications where continuity of torque and position estimation is essential.

5.5 Summary

This chapter presents a robust position sensor error-resilient control strategy for a dual-PMSM, AWD electric powertrain, wherein the rear, more powerful motor operates under sensorless control in the event of a position sensor failure. The proposed solution leverages a hyperbolic tangent-based SMO to accurately estimate the rotor position under dynamic conditions. To address the inherent challenges of sensorless (SMO) estimation at low speeds and during uphill transitions, the strategy exploits the electronically coordinated architecture of the dual-motor system by utilizing the front motor's vehicle speed feedback to enhance observer convergence. A blended weighting control algorithm ensures a seamless transition between sensor-based and sensorless modes, synchronizing the estimated position with the last known rotor position to minimize torque ripple and performance degradation.

The simulation studies have demonstrated the effectiveness of the proposed control framework across multiple challenging scenarios.

- 1) The blended-weighting transition strategy ensured seamless handover during sensor failures, constraining torque deviations to below 5% within a sub-10 ms latency.
- 2) The hyperbolic tangent-based SMO proved robust against parameter uncertainties and measurement noise, maintaining rotor angle estimation within 4° while significantly suppressing chattering, torque ripple, and EMI compared to conventional approaches.
- 3) At low speeds, the incorporation of front-axle reinforcement markedly improved observer convergence, reducing angle error by up to 67% and enabling smooth, low-jerk start-up performance even under slip conditions.

4) Furthermore, comparative benchmarking confirmed the superiority of the proposed method over extended Kalman filtering in terms of convergence speed, disturbance rejection, and computational efficiency, while fault recovery studies validated the resilience of the gradual reweighting strategy in achieving seamless reconnection.

Collectively, these results establish the proposed approach as a robust, efficient, and practical solution for dual-PMSM sensorless traction drives. Overall, the chapter contributes a significant advancement in fault-resilient control for dual-PMSM EV drivetrains, enabling continued high-performance operation under adverse conditions. The proposed framework aligns well with the safety, reliability, and performance requirements of next-generation electric mobility systems.

While Chapter 5 addresses position sensor failure rather than CME, it represents the logical culmination of the thesis's focus on resilience from sensor malfunctions. Chapter 3 and 4 demonstrate how to handle gradual sensor degradation in single and multi-motor configurations. Chapter 5 addresses the worst-case scenario, complete sensor loss, and proposes an observer-based solution that relies on accurate current measurements enabled by methods in previous chapters. Together, the three chapters provide a comprehensive safety framework covering different classes of sensor imperfections, from gradual degradation to complete failure, and demonstrate software-based mitigation techniques that could complement, or in some cases, reduce reliance on hardware redundancy.

Chapter 6 Conclusions and Future Work

6.1 Conclusions

Despite the rapid and exponential growth of EVs in recent years, the development of safety and performance enhancement technologies has not kept pace. Critical challenges persist, particularly in managing and mitigating electric powertrain errors that compromise performance and reduce components' lifespan. This disparity underscores the pressing need for more mature and robust safety solutions to ensure the long-term reliability and sustainability of EV technology. In this research the sources of error amongst some of the most critical powertrain components are addressed, most importantly, how errors within these units severely disrupt/destabilize closed-loop control, ultimately degrading performance and posing safety risks, necessitating robust error-resilient designs for reliable operation. Electric powertrain errors have amplified consequences in multi-motor EVs due to the interdependence of motors (for traction, stability, and efficiency) and control complexity. Failures impact not just performance but also safety, making fault tolerance a top priority. Advanced control strategies, redundancy, and real-time diagnostics are essential for reliable control. As such, this dissertation has proposed innovatively effective error-suppression algorithms applicable for use in both single and multi-motor frameworks. The primary contributions of this study can be summarized as follows:

In Chapter 2, a comprehensive literature review on the origins of error within crucial powertrain elements is discussed. A huge aspect of the review delves into the inevitability of the existence of errors when pivotal components like power inverters and position sensors operate in normal fashion as well as in gracefully degraded modes (enabling the vehicle to continue operation, albeit at reduced performance). During regular operation, inverter errors such as timing mismatches can lead to suboptimal modulation, increased losses, thus reducing system efficiency and accelerating component wear. Likewise, position sensor errors, stemming from drift, noise or misalignment compromise rotor position estimation, leading to torque ripple, reduced accuracy and degraded performance. In fault-tolerant modes, these errors have amplified consequences. Inverter mishaps may force derated operation or activate reconfiguration schemes which can maintain drive functionality but at the cost of reduced efficiency and increased thermal loading. Position sensor failures necessitate sensorless control

or redundant sensing strategies, which may offer limited precision, affecting dynamic response and potentially endangering operational safety. Thus, robust fault detection, isolation and mitigation strategies are essential to preserve performance and ensure safety and reliable operation across all modes. However, achieving accurate fault diagnosis in both normal and fault-tolerant modes demands high-fidelity models, adaptive thresholds, and rapid response mechanisms. Additionally, ensuring seamless fault recovery without performance degradation requires sophisticated control algorithms and redundancy management. These challenges highlight the need for advanced signal processing, machine learning techniques and resilient control architectures to enhance reliability and safety.

In chapter 3, a hybrid error compensation strategy that integrates an E-ASHA algorithm into an FCS-MPCC framework, targeting SPMSM drives was discussed. The discussion addresses the pervasive issue of hybrid errors (comprising current sensor inaccuracies and analog/digital delays) that detrimentally affect control precision, leading to degraded torque production, reduced system efficiency, and increased energy consumption. The proposed methodology introduces the E-ASHA scheme as a lightweight, non-invasive adaptive filtering solution that selectively cancels harmonics in the dq-axis current signals, responsible for speed and torque ripples. It employs the LMS adaptation technique to dynamically update filter coefficients, enabling real-time suppression of disturbance frequencies without the need for complex observers or additional sensors. A key innovation lies in the dual-path harmonic compensation, where the E-ASHA scheme addresses both q-axis and d-axis distortions, thereby ensuring comprehensive torque ripple minimization and enhanced motor speed smoothness. The integration preserves the stability of the existing control loop and enhances the robustness of the system under both steady-state and transient conditions.

In chapter 4, a novel correlative correction methodology to address CMEs in quad-motor electric drivetrains is presented. Recognizing that CMEs in such systems lead to compounded speed and torque ripple due to inter-motor dependencies, a DCA that individually calibrates each motor's current sensor while temporarily disabling the others to eliminate crosstalk and mutual interference is introduced. Unlike traditional observed-based or filter-intensive solutions, the proposed strategy employs a five-segment adjustable PWM scheme to strategically position sampling points at the midpoints of selected switching cycles. This enables efficient estimation and correction of both offset and scaling errors without altering routine control sampling routines or requiring additional sensors. By leveraging the logical

relationships between phase and DC-bus currents during specific inverter switching states, the method estimates and balances gain coefficients and offset values with minimal computational overhead. The study further addresses practical implementation issues, such as sampling time constraints and immeasurable regions in the PMW cycle, ensuring real-time feasibility.

Chapter 5 introduced a robust and fault-tolerant control framework for dual-PMSM, AWD EV systems, specifically addressing the challenge of rotor position sensor failure in the rear (more powerful) motor. A hyperbolic tangent-based SMO is utilized to estimate the rotor position and replace the failed sensor, delivering enhanced resilience to parameter variations and measurement noise. A major innovation of this work is the utilization of vehicle-level dynamics and real-time front motor data to assist in the rear motor's sensorless estimation process, enabling more accurate low-speed operation and improving estimator convergence. To ensure operational continuity during sensor failure, a novel blended weighting transition algorithm is further proposed. This strategy adaptively fuses sensor-based and observer-based feedback using dynamic confidence levels and exponential decay, facilitating seamless transitions with minimal torque ripple or control disruption. Error detection mechanisms based on signal characteristics and residual analysis trigger these transitions, while synchronization techniques ensure speed and position alignment before switching modes.

Principally, with respect to the topic of safety enhancement technologies for EVs, with special emphasis on electric powertrain errors, this dissertation examines the sources of error among chief powertrain components during regular and irregular modes of operation and develops effective strategies to curb these errors via theoretical analysis coupled with simulation/experimental validation. The study accomplished the following results:

- An extensive review of electric drivetrain errors and the need to capture these errors in their nascent stages within the intrinsically complex propulsion system.
- Developing a unified, efficient and scalable solution to motor drive hybrid errors via an E-ASHA scheme, with promising implications for real-time applications across a vast expanse within the electrified mobility industry.
- Development of a mutual corrective algorithm for CMEs within quad-motor electrified platforms.
- Proposal of an error-resilient control architecture for dual-PMSM, AWD, EV drivelines, enabling continued high-performance operation under adverse conditions. The

proposed framework aligns well with the safety, reliability and performance requirements of the next-generation electric mobility systems.

6.2 Future Research

Though this research makes significant contributions with respect to safety and performance enhancement for EVs, the complexity and the ever-evolving nature of these propulsion systems imply there is always more to uncover. Limitations in time, tools and scope naturally prevent complete coverage. Since the findings within this research hint at limitations in current safety enhancement technologies (such as sensor precision issues, thermal reliability in inverters, and software-hardware integration flaws), the information within this section can be an effective yardstick for future researchers seeking to build on these results and help outline where studies within this area of academics should head next. As such, future research could be conducted in the following areas:

❖ **Intelligent error prediction and compensation**

As electric powertrains operate under dynamic load conditions and harsh environments, traditional error compensation techniques, especially those dependent on fixed system parameters, often fall short. Intelligent error prediction and compensation represent a paradigm shift from static, model-driven approaches to adaptive, data-driven methods. Future research should explore the use of machine learning algorithms, adaptive observers and predictive control schemes that can learn system behaviour over time, anticipate the onset of errors and proactively mitigate their effects. For instance, integrating neural networks or support vector machines with powertrain control systems can allow for real-time estimation of non-linear error patterns such as dead-time distortion, resolver drift, or current sensor offset under variable operating conditions. Coupling these models with reinforcement learning or model predictive control (MPC) could enable self-tuning compensators that adapt based on feedback, rather than predefined models. This direction would significantly improve performance robustness and system safety, especially in transient and zero-crossing regions where classical compensators underperform.

❖ **Multi-harmonic and multi-disturbance handling**

The current implementation of the E-ASHA strategy targets the selective elimination of single-frequency harmonics within the dq-axis currents. However, real-world PMSM drive systems frequently encounter multiple simultaneous disturbances, including both low- and high-order harmonics, parameter variations, and time-varying disturbances induced by dynamic loading, rotor eccentricities, and mechanical vibrations. To address this complexity, future work should explore the development of multi-band adaptive compensation schemes that can detect and suppress multiple harmonic components concurrently without degrading system responsiveness or stability. Promising directions include:

- **Multichannel or multi-band adaptive filtering architectures** that can estimate multiple frequency components in parallel, enabling simultaneous cancellation of several harmonics.
- **Spectral estimation and tracking techniques**, such as Prony's method, frequency-locked loops or adaptive Fourier decomposition to identify dominant disturbances in real-time.
- **Time-varying harmonic modelling** to accommodate disturbances whose frequencies change with operating conditions such as motor speed or load torque.
- **Disturbance observers coupled with predictive algorithms**, allowing the system to anticipate compound disturbances and apply proactive compensation strategies.

❖ **Extension of correlative correction strategy to dynamic and load-varying conditions**

The current correlative correction strategy achieves precise CME calibration by temporarily isolating each motor within the quad-motor drivetrain during the correction process. While this approach is effective under low-variability conditions, real-world EV operations are inherently dynamic, involving frequent load changes, regenerative braking, terrain variations, and simultaneous torque demands across all motors. These scenarios challenge the feasibility of sequential motor isolation and fixed calibration schedules. Future research should aim to develop an online or continuous calibration framework capable of estimating and correcting CMEs in real-time without interrupting motor operations. This would involve exploring adaptive modulation techniques and predictive algorithms that can operate under transient states, such as acceleration,

deceleration, and dynamic torque redistribution. Additionally, the interplay between CMEs and mechanical disturbances (such as load inertia shifts or wheel slippage) should be studied to develop robust error compensation schemes that maintain accuracy under non-ideal conditions. Such advancements would significantly enhance the real-time reliability and control precision of QMD systems deployed in unpredictable driving environments.

❖ **Enhanced low-speed estimation accuracy**

According to Chapter 5, one of the principal limitations of sensorless control strategies such as the SMO approach is diminished estimation precision at low or zero rotor speeds, particularly in the presence of slip, traction loss, or low excitation conditions. Although the use of front motor speed and vehicle dynamics helped mitigate these limitations, performance remains suboptimal during low-speed start-up or under variable road friction. Future research could focus on hybrid observer strategies that fuse SMOs with alternative techniques such as high-frequency signal injection (HFI) or model reference adaptive system (MRAS). These hybrid models may exploit the complementary strengths of different estimation methods to maintain stable and accurate position/speed estimates across the full operating range. Additionally, advanced signal processing techniques to dynamically compensate for phase delay, DC offsets, or signal degradation can further enhance estimation fidelity in low-speed regimes.

References

- [1] “Global EV Outlook 2025 – Analysis,” IEA. Accessed: Sep. 06, 2025. [Online]. Available: <https://www.iea.org/reports/global-ev-outlook-2025>
- [2] A. Wireko-Brobby, Y. Hu, G. Wang, C. Gong, W. Lang, and Z. Zhang, “Analysis of the Sources of Error Within PMSM-Based Electric Powertrains—A Review,” *IEEE Trans. Transp. Electrification*, vol. 10, no. 3, pp. 6370–6406, Sep. 2024, doi: 10.1109/TTE.2023.3337865.
- [3] C. Liu, K. T. Chau, C. H. T. Lee, and Z. Song, “A Critical Review of Advanced Electric Machines and Control Strategies for Electric Vehicles,” *Proc. IEEE*, vol. 109, no. 6, pp. 1004–1028, Jun. 2021, doi: 10.1109/JPROC.2020.3041417.
- [4] I. Ahmed, W. Hassan, M. Negnevitsky, E. Franklin, and M. Adnan, “Robust Dual Loop Nonlinear Controller for Four-Phase Interleaved Boost Converter in Fuel Cell Electric Vehicle Applications,” *IEEE Trans. Ind. Electron.*, pp. 1–13, 2026, doi: 10.1109/TIE.2025.3647923.
- [5] C. Gong, Y. R. Li, and N. R. Zargari, “An Overview of Advancements in Multimotor Drives: Structural Diversity, Advanced Control, Specific Technical Challenges, and Solutions,” *Proc. IEEE*, vol. 112, no. 3, pp. 184–209, Mar. 2024, doi: 10.1109/JPROC.2024.3387061.
- [6] Z. Li, C. Li, Y. Wang, G. Wang, and D. Xu, “EHMAFO-Based Sensorless Control of PMSM Using Dual-LESO for Position Error and Disturbance Compensation,” *IEEE Trans. Ind. Electron.*, pp. 1–12, 2026, doi: 10.1109/TIE.2026.3663795.
- [7] H. Yang, L. Tao, J. Wang, Z. Li, and L. Zhou, “Discrete-Time Speed-Independent Current Control for Zero Tracking Error in Low-Inertia PMSM Drives,” *IEEE Trans. Ind. Electron.*, pp. 1–13, 2026, doi: 10.1109/TIE.2025.3647873.
- [8] “What Is ISO 26262? A Guide to Functional Safety in Automotive,” Jama Software. Accessed: Jul. 26, 2026. [Online]. Available: <https://www.jamasoftware.com/requirements-management-guide/automotive-engineering/iso-26262/>
- [9] T. Zhang, Y. Mao, Y. Zhang, X. Chen, Z. Wang, and X. Wang, “Parameter Identification-Based Diagnosis of Open-Circuit Fault in Dual Three-Phase PMSM Drives,” *IEEE Trans. Transp. Electrification*, vol. 12, no. 1, pp. 159–167, Feb. 2026, doi: 10.1109/TTE.2025.3611939.
- [10] L. Chen, M. Chen, B. Li, X. Sun, and F. Jiang, “Open-Circuit Fault Diagnosis Method for Dual Three-Phase PMSM Drives Based on Common and Distinctive Features of Improved Fault Indices,” *IEEE Trans. Transp. Electrification*, vol. 12, no. 2, pp. 3292–3306, Apr. 2026, doi: 10.1109/TTE.2025.3646825.
- [11] P. Pietrzak, M. Wolkiewicz, and T. Orłowska-Kowalska, “PMSM Stator Winding Fault Detection and Classification Based on Bispectrum Analysis and Convolutional Neural Network,” *IEEE Trans. Ind. Electron.*, vol. 70, no. 5, pp. 5192–5202, May 2023, doi: 10.1109/TIE.2022.3189076.
- [12] Z. Tabarniarami, M. Ghods, J. Faiz, and M. Abedini, “Online Diagnosis of Short-Circuit Faults of Permanent Magnet Synchronous Generator by Short-Time Analysis of the Three Phase Amplitude-Phase Signal Based on Analytical Modeling,” *IEEE Trans. Transp. Electrification*, vol. 10, no. 4, pp. 10029–10042, Dec. 2024, doi: 10.1109/TTE.2024.3369970.

- [13] B. Jung, P. Jang, K. Nam, and Y. Kim, "Overmodulation Strategy for Torque Balance of Dual-Motor Systems Considering Angle Offset," *IEEE Trans. Ind. Appl.*, vol. 58, no. 6, pp. 6869–6878, Nov. 2022, doi: 10.1109/TIA.2022.3198382.
- [14] T. Liu, Z. Liu, and F. Zhu, "A Nonlinear Robust Speed Controller for Dual Nonidentical Parallel PMSM System," *IEEE Trans. Power Electron.*, vol. 37, no. 9, pp. 10190–10199, Sep. 2022, doi: 10.1109/TPEL.2022.3157140.
- [15] J. Hang, J. Zhang, H. Qin, S. Ding, Y. Huang, and W. Hua, "A Simplified Model Predictive Voltage Control for Three-Phase Four-Switch Inverter-Fed PMSM Drives With Capacitor Voltage Offset Suppression and Current Ripple Reduction," *IEEE Trans. Power Electron.*, vol. 38, no. 4, pp. 5154–5166, Apr. 2023, doi: 10.1109/TPEL.2022.3225831.
- [16] W. Chen, L. Zhu, S. Wang, X. Li, T. Shi, and C. Xia, "Rotating Restart Method for TPFS Inverter-Fed Sensorless PMSM Drive System Based on Dual Effective Voltage Vectors Injection," *IEEE Trans. Power Electron.*, vol. 39, no. 9, pp. 11708–11722, Sep. 2024, doi: 10.1109/TPEL.2024.3416463.
- [17] S. Li, X. Zhang, X. Liu, and H. Su, "Adaptive Robust Sensorless Control for PMSM Based on a Wavelet Neural Network Back EMF Observer and Extended State Observer," *IEEE Trans. Power Electron.*, pp. 1–10, 2026, doi: 10.1109/TPEL.2026.3676897.
- [18] X. Guo, H. Min, S. Shi, and Y. Hu, "Prescribed-Time Speed Control for Sensorless PMSM Using a Novel Third-Order Super-Twisting Extended State Observer-Based Approach," *IEEE Trans. Ind. Electron.*, vol. 73, no. 5, pp. 7749–7758, May 2026, doi: 10.1109/TIE.2025.3642389.
- [19] J. Hang, X. Shu, S. Ding, and Y. Huang, "Robust Open-Circuit Fault Diagnosis for PMSM Drives Using Wavelet Convolutional Neural Network With Small Samples of Normalized Current Vector Trajectory Graph," *IEEE Trans. Ind. Electron.*, vol. 70, no. 8, pp. 7653–7663, Aug. 2023, doi: 10.1109/TIE.2022.3231304.
- [20] W. Wang, Y. Mao, P. Cui, J. Fu, W. Hua, and M. Cheng, "Double Normalization Fault Diagnosis Method for Open-Circuit Faults of PMSM Drives," *IEEE Trans. Power Electron.*, vol. 39, no. 9, pp. 11613–11624, Sep. 2024, doi: 10.1109/TPEL.2024.3404402.
- [21] S. Ding, W. He, and J. Hang, "Uniform Demagnetization Fault Diagnosis of PMSM Based on Radial Air-Gap Flux Density Under Nonstationary Conditions," *IEEE Trans. Transp. Electrification*, vol. 11, no. 2, pp. 6690–6699, Apr. 2025, doi: 10.1109/TTE.2024.3515114.
- [22] W. He, J. Hang, S. Ding, L. Sun, and W. Hua, "Robust Diagnosis of Partial Demagnetization Fault in PMSMs Using Radial Air-Gap Flux Density Under Complex Working Conditions," *IEEE Trans. Ind. Electron.*, vol. 71, no. 10, pp. 12001–12010, Oct. 2024, doi: 10.1109/TIE.2024.3349520.
- [23] K. Yan, M. Yang, Z. Hu, J. Li, L. Xu, and M. Ouyang, "Parameter Matching Principle for Dual-Rotor In-Wheel Motors via Coupling Effect Exploitation," *IEEE Trans. Ind. Electron.*, pp. 1–13, 2026, doi: 10.1109/TIE.2026.3651365.
- [24] T. M. Jahns and B. Sarlioglu, "The Incredible Shrinking Motor Drive: Accelerating the Transition to Integrated Motor Drives," *IEEE Power Electron. Mag.*, vol. 7, no. 3, pp. 18–27, Sep. 2020, doi: 10.1109/MPEL.2020.3011275.
- [25] S. K. Kakodia and G. Dyanamina, "Implementation of FPGA-Based Neural Network Controller for Reducing Speed Ripple for a PMSM-Driven EV Using MRAS Speed Estimator," *IEEE Trans. Artif. Intell.*, vol. 7, no. 2, pp. 684–695, Feb. 2026, doi: 10.1109/TAI.2025.3571702.

- [26] N. Kaminski *et al.*, “Reliability of Wide Bandgap Semiconductors for Automotive Applications,” *IEEE Trans. Electron Devices*, pp. 1–16, 2026, doi: 10.1109/TED.2026.3672721.
- [27] M. Hassani Sadi, Z. Sadeghi, and J. Bauman, “A Comprehensive Review of Universal Fast-Charging Techniques for 400-V and 800-V Electric Vehicles,” *IEEE Access*, vol. 13, pp. 153212–153233, 2025, doi: 10.1109/ACCESS.2025.3603845.
- [28] C. C. Chan, “The State of the Art of Electric, Hybrid, and Fuel Cell Vehicles,” *Proc. IEEE*, vol. 95, no. 4, pp. 704–718, Apr. 2007, doi: 10.1109/JPROC.2007.892489.
- [29] E. Osmanbasic, “The Many Types of EV Motors,” Engineering.com. Accessed: Jun. 21, 2023. [Online]. Available: <https://www.engineering.com/story/the-many-types-of-ev-motors>
- [30] C. Parag Jose and S. Meikandasivam, “A Review on the Trends and Developments in Hybrid Electric Vehicles,” in *Innovative Design and Development Practices in Aerospace and Automotive Engineering*, R. P. Bajpai and U. Chandrasekhar, Eds., in Lecture Notes in Mechanical Engineering. Singapore: Springer, 2017, pp. 211–229. doi: 10.1007/978-981-10-1771-1_25.
- [31] T. Wu, “Safety Improvement Techniques for Electric Vehicle Powertrains”.
- [32] J. Dong *et al.*, “Hybrid Acoustic Noise Analysis Approach of Conventional and Mutually Coupled Switched Reluctance Motors,” *IEEE Trans. Energy Convers.*, vol. 32, no. 3, pp. 1042–1051, Sep. 2017, doi: 10.1109/TEC.2017.2672741.
- [33] C. Li, G. Wang, G. Zhang, N. Zhao, Y. Gao, and D. Xu, “Torque Ripples Minimization of Sensorless SynRM Drives for Low-Speed Operation Using Bi-HFSI Scheme,” *IEEE Trans. Ind. Electron.*, vol. 68, no. 7, pp. 5559–5570, Jul. 2021, doi: 10.1109/TIE.2020.2996133.
- [34] J. Zheng, Z. Wang, D. Wang, Y. Li, and M. Li, “Review of fault diagnosis of PMSM drive system in electric vehicles,” in *2017 36th Chinese Control Conference (CCC)*, Jul. 2017, pp. 7426–7432. doi: 10.23919/ChiCC.2017.8028529.
- [35] Y. Wang, K. Liu, W. Hua, C. Zhang, Z. Wu, and H. Zhang, “Analysis and Detection of Rotor Eccentricity in Permanent Magnet Synchronous Machines Based on Linear Hall Sensors,” *IEEE Trans. Power Electron.*, vol. 37, no. 4, pp. 4719–4729, Apr. 2022, doi: 10.1109/TPEL.2021.3131576.
- [36] M. A. Awadallah and M. M. Morcos, “Application of AI tools in fault diagnosis of electrical machines and drives-an overview,” *IEEE Trans. Energy Convers.*, vol. 18, no. 2, pp. 245–251, Jun. 2003, doi: 10.1109/TEC.2003.811739.
- [37] C. Ma, J. Li, N. Zhang, F. Bu, and Z. Yang, “Open-Circuit Radial Stray Magnetic Flux Density Based Non-invasive Diagnosis for Mixed Eccentricity Parameters of Interior Permanent Magnet Synchronous Motors in Electric Vehicles,” *IEEE Trans. Ind. Electron.*, pp. 1–1, 2022, doi: 10.1109/TIE.2022.3165250.
- [38] S. Nandi, H. A. Toliyat, and X. Li, “Condition Monitoring and Fault Diagnosis of Electrical Motors—A Review,” *IEEE Trans. Energy Convers.*, vol. 20, no. 4, pp. 719–729, Dec. 2005, doi: 10.1109/TEC.2005.847955.
- [39] B. Bossoufi, M. Karim, A. Lagrioui, and S. Ionit , “Performance analysis of Direct Torque Control (DTC) for synchronous machine permanent magnet (PMSM),” in *2010 IEEE 16th International Symposium for Design and Technology in Electronic Packaging (SIITME)*, Sep. 2010, pp. 237–242. doi: 10.1109/SIITME.2010.5649125.
- [40] S. Rafa, A. Larabi, L. Hocine, and L. Barazane, “Control techniques for permanent magnet synchronous motor drive,” in *18th Mediterranean Conference on Control and Automation, MED’10*, Jun. 2010, pp. 1115–1120. doi: 10.1109/MED.2010.5547644.

- [41] S. Agoro and I. Husain, "Robust Deadbeat Finite-Set Predictive Current Control With Torque Oscillation and Noise Reduction for PMSM Drives," *IEEE Trans. Ind. Appl.*, vol. 58, no. 1, pp. 365–374, Jan. 2022, doi: 10.1109/TIA.2021.3130022.
- [42] A. Dearien, "HEV/EV Traction Inverter Design Guide Using Isolated IGBT and SiC Gate Drivers," p. 36, 2019.
- [43] Z. Wu *et al.*, "Dead-Time Compensation Based on a Modified Multiple Complex Coefficient Filter for Permanent Magnet Synchronous Machine Drives," *IEEE Trans. Power Electron.*, vol. 36, no. 11, pp. 12979–12989, Nov. 2021, doi: 10.1109/TPEL.2021.3078167.
- [44] S. Suroso, D. T. Nugroho, and T. Noguchi, "New Dead-Time Compensation Method of Power Inverter using Carrier Based Sinusoidal Pulse-Width Modulation," *Int. J. Electr. Comput. Eng. IJECE*, vol. 8, no. 6, p. 4880, Dec. 2018, doi: 10.11591/ijece.v8i6.pp4880-4891.
- [45] Tadano Y., Urushibata S., Ogura K., Shigaki A., and Nomura M., "A Multilevel PWM Strategy suitable for High-Voltage Motor Direct Drive Systems in Consideration of the Adverse Effect of a Deadtime," *IEEJ Trans. Ind. Appl.*, vol. 126, no. 1, pp. 1–9, 2006, doi: 10.1541/ieejias.126.1.
- [46] J.-W. Choi and S.-K. Sul, "Inverter output voltage synthesis using novel dead time compensation," *IEEE Trans. Power Electron.*, vol. 11, no. 2, pp. 221–227, Mar. 1996, doi: 10.1109/63.486169.
- [47] D. Chatterjee, C. Chakraborty, and S. Dalapati, "An Overview on Dead-Time Distortion and Its Correction in PWM Inverters," *IEEE Open J. Power Electron.*, vol. 6, pp. 1453–1490, 2025, doi: 10.1109/OJPEL.2025.3600262.
- [48] J. Zhou, K. Liu, J. Li, L. Li, W. Hu, and R. Ding, "VSI Nonlinearity Compensation of a PMSM Drive System Using Deadbeat Prediction Based Current Zero-Crossing Detection," *World Electr. Veh. J.*, vol. 12, no. 1, p. 17, Jan. 2021, doi: 10.3390/wevj12010017.
- [49] K. Yu and Z. Wang, "An Online Compensation Method of VSI Nonlinearity for Dual Three-Phase PMSM Drives Using Current Injection," *IEEE Trans. Power Electron.*, vol. 37, no. 4, pp. 3769–3774, Apr. 2022, doi: 10.1109/TPEL.2021.3127990.
- [50] D.-H. Lee and J.-W. Ahn, "A Simple and Direct Dead-Time Effect Compensation Scheme in PWM-VSI," *IEEE Trans. Ind. Appl.*, vol. 50, no. 5, pp. 3017–3025, Sep. 2014, doi: 10.1109/TIA.2014.2303932.
- [51] Z. Shen and D. Jiang, "Dead-Time Effect Compensation Method Based on Current Ripple Prediction for Voltage-Source Inverters," *IEEE Trans. Power Electron.*, vol. 34, no. 1, pp. 971–983, Jan. 2019, doi: 10.1109/TPEL.2018.2820727.
- [52] A. R. Munoz and T. A. Lipo, "On-line dead-time compensation technique for open-loop PWM-VSI drives," *IEEE Trans. Power Electron.*, vol. 14, no. 4, pp. 683–689, Jul. 1999, doi: 10.1109/63.774205.
- [53] A. Lewicki, "Dead-Time Effect Compensation Based on Additional Phase Current Measurements," *IEEE Trans. Ind. Electron.*, vol. 62, no. 7, pp. 4078–4085, Jul. 2015, doi: 10.1109/TIE.2015.2389756.
- [54] J. Zhang and F. L. Luo, "An accurate approach of dead-time compensation for three-phase DC/AC inverter," in *2009 4th IEEE Conference on Industrial Electronics and Applications*, May 2009, pp. 2929–2934. doi: 10.1109/ICIEA.2009.5138745.
- [55] Z. Zhang and L. Xu, "Dead-Time Compensation of Inverters Considering Snubber and Parasitic Capacitance," *IEEE Trans. Power Electron.*, vol. 29, no. 6, pp. 3179–3187, Jun. 2014, doi: 10.1109/TPEL.2013.2275551.

- [56] Y. Park and S.-K. Sul, "Implementation Schemes to Compensate for Inverter Nonlinearity Based on Trapezoidal Voltage," *IEEE Trans. Ind. Appl.*, vol. 50, no. 2, pp. 1066–1073, Mar. 2014, doi: 10.1109/TIA.2013.2272431.
- [57] D. E. Salt, D. Drury, D. Holliday, A. Griffo, P. Sangha, and A. Dinu, "Compensation of Inverter Nonlinear Distortion Effects for Signal-Injection-Based Sensorless Control," *IEEE Trans. Ind. Appl.*, vol. 47, no. 5, pp. 2084–2092, Sep. 2011, doi: 10.1109/TIA.2011.2161430.
- [58] G. Shen, W. Yao, B. Chen, K. Wang, K. Lee, and Z. Lu, "Automeasurement of the Inverter Output Voltage Delay Curve to Compensate for Inverter Nonlinearity in Sensorless Motor Drives," *IEEE Trans. Power Electron.*, vol. 29, no. 10, pp. 5542–5553, Oct. 2014, doi: 10.1109/TPEL.2013.2293134.
- [59] T. Mannen and H. Fujita, "Dead-Time Compensation Method Based on Current Ripple Estimation," *IEEE Trans. Power Electron.*, vol. 30, no. 7, pp. 4016–4024, Jul. 2015, doi: 10.1109/TPEL.2014.2352716.
- [60] W. Dafang, Y. Bowen, Z. Cheng, Z. Chuanwei, and Q. ji, "A Feedback-Type Phase Voltage Compensation Strategy Based on Phase Current Reconstruction for ACIM Drives," *IEEE Trans. Power Electron.*, vol. 29, no. 9, pp. 5031–5043, Sep. 2014, doi: 10.1109/TPEL.2013.2285399.
- [61] Y.-K. Lin and Y.-S. Lai, "Dead-Time Elimination of PWM-Controlled Inverter/Converter Without Separate Power Sources for Current Polarity Detection Circuit," *IEEE Trans. Ind. Electron.*, vol. 56, no. 6, pp. 2121–2127, Jun. 2009, doi: 10.1109/TIE.2009.2014305.
- [62] Y. Murai, T. Watanabe, and H. Iwasaki, "Waveform Distortion and Correction Circuit for PWM Inverters with Switching Lag-Times," *IEEE Trans. Ind. Appl.*, vol. IA-23, no. 5, pp. 881–886, Sep. 1987, doi: 10.1109/TIA.1987.4504998.
- [63] D. Leggate and R. J. Kerkman, "Pulse-based dead-time compensator for PWM voltage inverters," *IEEE Trans. Ind. Electron.*, vol. 44, no. 2, pp. 191–197, Apr. 1997, doi: 10.1109/41.564157.
- [64] J.-L. Lin, "A new approach of dead-time compensation for PWM voltage inverters," *IEEE Trans. Circuits Syst. Fundam. Theory Appl.*, vol. 49, no. 4, pp. 476–483, Apr. 2002, doi: 10.1109/81.995662.
- [65] D. B. Rathnayake, S. M. H. K. Samarasinghe, C. I. Medagedara, and S. G. Abeyratne, "An enhanced pulse-based dead-time compensation technique for PWM-VSI drives," in *2014 9th International Conference on Industrial and Information Systems (ICIIS)*, Dec. 2014, pp. 1–5. doi: 10.1109/ICIINFS.2014.7036532.
- [66] Y. Zhao, W. Qiao, and L. Wu, "Dead-time effect and current regulation quality analysis for a sliding-mode position observer-based sensorless IPMSM drives," in *2012 IEEE Industry Applications Society Annual Meeting*, Oct. 2012, pp. 1–7. doi: 10.1109/IAS.2012.6374042.
- [67] V. Blahník, Z. Peroutka, J. Žák, and J. Talla, "Elimination of dead-time effect causing current distortion of single-phase power converters," in *2012 15th International Power Electronics and Motion Control Conference (EPE/PEMC)*, Sep. 2012, p. DS1e.3-1-DS1e.3-6. doi: 10.1109/EPEPEMC.2012.6397243.
- [68] Ü. Büyükeleş and A. Ersak, "Analysis and compensation of nonlinear effects in an inverter with power MOSFETs," in *2012 15th International Power Electronics and Motion Control Conference (EPE/PEMC)*, Sep. 2012, p. DS2c.3-1-DS2c.3-6. doi: 10.1109/EPEPEMC.2012.6397287.

- [69] G. Wang, R. Yang, and D. Xu, "DSP-Based Control of Sensorless IPMSM Drives for Wide-Speed-Range Operation," *IEEE Trans. Ind. Electron.*, vol. 60, no. 2, pp. 720–727, Feb. 2013, doi: 10.1109/TIE.2012.2205360.
- [70] S. Jin and Y. Zhong, "A novel three-level SVPWM algorithm considering neutral-point control, narrow-pulse elimination and dead-time compensation," in *The 4th International Power Electronics and Motion Control Conference, 2004. IPEMC 2004.*, Aug. 2004, pp. 688–693 Vol.2.
- [71] C. Attaianesi and G. Tomasso, "Predictive compensation of dead-time effects in VSI feeding induction motors," *IEEE Trans. Ind. Appl.*, vol. 37, no. 3, pp. 856–863, May 2001, doi: 10.1109/28.924768.
- [72] G. Liu, D. Wang, Y. Jin, M. Wang, and P. Zhang, "Current-Detection-Independent Dead-Time Compensation Method Based on Terminal Voltage A/D Conversion for PWM VSI," *IEEE Trans. Ind. Electron.*, vol. 64, no. 10, pp. 7689–7699, Oct. 2017, doi: 10.1109/TIE.2017.2696480.
- [73] L. Chen and F. Z. Peng, "Dead-Time Elimination for Voltage Source Inverters," *IEEE Trans. Power Electron.*, vol. 23, no. 2, pp. 574–580, Mar. 2008, doi: 10.1109/TPEL.2007.915766.
- [74] X. Zhang, Y. Cheng, Z. Zhao, and K. Yan, "Optimized Model Predictive Control With Dead-Time Voltage Vector for PMSM Drives," *IEEE Trans. Power Electron.*, vol. 36, no. 3, pp. 3149–3158, Mar. 2021, doi: 10.1109/TPEL.2020.3012985.
- [75] Z. Zhang, H. Lu, D. J. Costinett, F. Wang, L. M. Tolbert, and B. J. Blalock, "Model-Based Dead Time Optimization for Voltage-Source Converters Utilizing Silicon Carbide Semiconductors," *IEEE Trans. Power Electron.*, vol. 32, no. 11, pp. 8833–8844, Nov. 2017, doi: 10.1109/TPEL.2016.2645578.
- [76] N. Bedetti, S. Calligaro, and R. Petrella, "Self-Commissioning of Inverter Dead-Time Compensation by Multiple Linear Regression Based on a Physical Model," *IEEE Trans. Ind. Appl.*, vol. 51, no. 5, pp. 3954–3964, Sep. 2015, doi: 10.1109/TIA.2015.2436882.
- [77] K. Liu and Z. Q. Zhu, "Online Estimation of the Rotor Flux Linkage and Voltage-Source Inverter Nonlinearity in Permanent Magnet Synchronous Machine Drives," *IEEE Trans. Power Electron.*, vol. 29, no. 1, pp. 418–427, Jan. 2014, doi: 10.1109/TPEL.2013.2252024.
- [78] S.-Y. Kim, W. Lee, M.-S. Rho, and S.-Y. Park, "Effective Dead-Time Compensation Using a Simple Vectorial Disturbance Estimator in PMSM Drives," *IEEE Trans. Ind. Electron.*, vol. 57, no. 5, pp. 1609–1614, May 2010, doi: 10.1109/TIE.2009.2033098.
- [79] H.-S. Kim, H.-T. Moon, and M.-J. Youn, "On-line dead-time compensation method using disturbance observer," *IEEE Trans. Power Electron.*, vol. 18, no. 6, pp. 1336–1345, Nov. 2003, doi: 10.1109/TPEL.2003.818833.
- [80] N. Urasaki, T. Senjyu, K. Uezato, and T. Funabashi, "Adaptive Dead-Time Compensation Strategy for Permanent Magnet Synchronous Motor Drive," *IEEE Trans. Energy Convers.*, vol. 22, no. 2, pp. 271–280, Jun. 2007, doi: 10.1109/TEC.2006.875469.
- [81] M. A. Herran, J. R. Fischer, S. A. Gonzalez, M. G. Judewicz, and D. O. Carrica, "Adaptive Dead-Time Compensation for Grid-Connected PWM Inverters of Single-Stage PV Systems," *IEEE Trans. Power Electron.*, vol. 28, no. 6, pp. 2816–2825, Jun. 2013, doi: 10.1109/TPEL.2012.2227811.
- [82] S.-Y. Kim and S.-Y. Park, "Compensation of Dead-Time Effects Based on Adaptive Harmonic Filtering in the Vector-Controlled AC Motor Drives," *IEEE Trans. Ind. Electron.*, vol. 54, no. 3, pp. 1768–1777, Jun. 2007, doi: 10.1109/TIE.2007.895132.

- [83] T. Qiu, X. Wen, and F. Zhao, "Adaptive-Linear-Neuron-Based Dead-Time Effects Compensation Scheme for PMSM Drives," *IEEE Trans. Power Electron.*, vol. 31, no. 3, pp. 2530–2538, Mar. 2016, doi: 10.1109/TPEL.2015.2427914.
- [84] S.-H. Hwang and J.-M. Kim, "Dead Time Compensation Method for Voltage-Fed PWM Inverter," *IEEE Trans. Energy Convers.*, vol. 25, no. 1, pp. 1–10, Mar. 2010, doi: 10.1109/TEC.2009.2031811.
- [85] Y. Yang, K. Zhou, H. Wang, and F. Blaabjerg, "Harmonics mitigation of dead time effects in PWM converters using a repetitive controller," in *2015 IEEE Applied Power Electronics Conference and Exposition (APEC)*, Mar. 2015, pp. 1479–1486. doi: 10.1109/APEC.2015.7104543.
- [86] B. A. Francis and W. M. Wonham, "The internal model principle for linear multivariable regulators," p. 25.
- [87] Z. Tang and B. Akin, "Suppression of Dead-Time Distortion Through Revised Repetitive Controller in PMSM Drives," *IEEE Trans. Energy Convers.*, vol. 32, no. 3, pp. 918–930, Sep. 2017, doi: 10.1109/TEC.2017.2679701.
- [88] J. Lu, Y. Hu, G. Chen, Z. Wang, and J. Liu, "Mutual Calibration of Multiple Current Sensors With Accuracy Uncertainties in IPMSM Drives for Electric Vehicles," *IEEE Trans. Ind. Electron.*, vol. 67, no. 1, pp. 69–79, Jan. 2020, doi: 10.1109/TIE.2019.2896320.
- [89] J. Lu, Y. Hu, J. Liu, K. Ni, and H. Wen, "Detrimental Effect Elimination of Current Sensor Accuracy Uncertainty for High-Precision Position Sensorless Control of Interior Permanent Magnet Synchronous Motor Drives," *IEEE Trans. Ind. Electron.*, vol. 67, no. 7, pp. 6101–6111, Jul. 2020, doi: 10.1109/TIE.2019.2938459.
- [90] F. R. Salmasi, "A Self-Healing Induction Motor Drive With Model Free Sensor Tampering and Sensor Fault Detection, Isolation, and Compensation," *IEEE Trans. Ind. Electron.*, vol. 64, no. 8, pp. 6105–6115, Aug. 2017, doi: 10.1109/TIE.2017.2682035.
- [91] H.-S. Jung, J.-M. Kim, C.-U. Kim, and C. Choi, "Diminution of current measurement error for vector controlled AC motor drives," in *IEEE International Conference on Electric Machines and Drives, 2005.*, May 2005, pp. 551–557. doi: 10.1109/IEMDC.2005.195777.
- [92] M. Kim, S.-K. Sul, and J. Lee, "Compensation of Current Measurement Error for Current-Controlled PMSM Drives," *IEEE Trans. Ind. Appl.*, vol. 50, no. 5, pp. 3365–3373, Sep. 2014, doi: 10.1109/TIA.2014.2301873.
- [93] J. Sorensen and D. O'Sullivan, "A System Approach to Understanding the Impact of Nonideal Effects in a Motor Drive Current Loop," p. 7.
- [94] J. Lu, Y. Hu, J. Liu, and H. Wen, "Self-Calibration of Phase Current Sensors With Sampling Errors by Multipoint Sampling of Current Values in a Single PWM Cycle," *IEEE Trans. Ind. Electron.*, vol. 68, no. 4, pp. 2942–2951, Apr. 2021, doi: 10.1109/TIE.2020.2982110.
- [95] Q. N. Trinh, P. Wang, Y. Tang, L. H. Koh, and F. H. Choo, "Compensation of DC Offset and Scaling Errors in Voltage and Current Measurements of Three-Phase AC/DC Converters," *IEEE Trans. Power Electron.*, vol. 33, no. 6, pp. 5401–5414, Jun. 2018, doi: 10.1109/TPEL.2017.2734809.
- [96] Q. N. Trinh, F. H. Choo, Y. Tang, and P. Wang, "Control Strategy to Compensate for Current and Voltage Measurement Errors in Three-Phase PWM Rectifiers," *IEEE Trans. Ind. Appl.*, vol. 55, no. 3, pp. 2879–2889, May 2019, doi: 10.1109/TIA.2019.2894107.
- [97] D.-W. Chung and S.-K. Sul, "Analysis and compensation of current measurement error in vector-controlled AC motor drives," *IEEE Trans. Ind. Appl.*, vol. 34, no. 2, pp. 340–345, Mar. 1998, doi: 10.1109/28.663477.

- [98] K.-W. Lee and S.-I. Kim, "Dynamic Performance Improvement of a Current Offset Error Compensator in Current Vector-Controlled SPMSM Drives," *IEEE Trans. Ind. Electron.*, vol. 66, no. 9, pp. 6727–6736, Sep. 2019, doi: 10.1109/TIE.2018.2877162.
- [99] Q. N. Trinh, P. Wang, Y. Tang, and F. H. Choo, "Mitigation of DC and Harmonic Currents Generated by Voltage Measurement Errors and Grid Voltage Distortions in Transformerless Grid-Connected Inverters," *IEEE Trans. Energy Convers.*, vol. 33, no. 2, pp. 801–813, Jun. 2018, doi: 10.1109/TEC.2017.2763240.
- [100] W. Qian, S. K. Panda, and J.-X. Xu, "Torque ripple minimization in PM synchronous motors using iterative learning control," *IEEE Trans. Power Electron.*, vol. 19, no. 2, pp. 272–279, Mar. 2004, doi: 10.1109/TPEL.2003.820537.
- [101] M. C. Harke, J. M. Guerrero, M. W. Degner, F. Briz, and R. D. Lorenz, "Current Measurement Gain Tuning Using High-Frequency Signal Injection," *IEEE Trans. Ind. Appl.*, vol. 44, no. 5, pp. 1578–1586, Sep. 2008, doi: 10.1109/TIA.2008.2002170.
- [102] G. Wang, J. Kuang, N. Zhao, G. Zhang, and D. Xu, "Rotor Position Estimation of PMSM in Low-Speed Region and Standstill Using Zero-Voltage Vector Injection," *IEEE Trans. Power Electron.*, vol. 33, no. 9, pp. 7948–7958, Sep. 2018, doi: 10.1109/TPEL.2017.2767294.
- [103] M. C. Harke and R. D. Lorenz, "The Spatial Effect and Compensation of Current Sensor Gain Deviation for Three-phase Three-wire Systems," in *APEC 07 - Twenty-Second Annual IEEE Applied Power Electronics Conference and Exposition*, Feb. 2007, pp. 435–441. doi: 10.1109/APEX.2007.357550.
- [104] K.-R. Cho and J.-K. Seok, "Correction on Current Measurement Errors for Accurate Flux Estimation of AC Drives at Low Stator Frequency," *IEEE Trans. Ind. Appl.*, vol. 44, no. 2, pp. 594–603, Mar. 2008, doi: 10.1109/TIA.2008.916730.
- [105] K.-R. Cho and J.-K. Seok, "Pure-Integration-Based Flux Acquisition With Drift and Residual Error Compensation at a Low Stator Frequency," *IEEE Trans. Ind. Appl.*, vol. 45, no. 4, pp. 1276–1285, Jul. 2009, doi: 10.1109/TIA.2009.2023487.
- [106] Y. Jeong, S.-K. Sul, S. E. Schulz, and N. R. Patel, "Fault detection and fault-tolerant control of interior permanent-magnet motor drive system for electric vehicle," *IEEE Trans. Ind. Appl.*, vol. 41, no. 1, pp. 46–51, Jan. 2005, doi: 10.1109/TIA.2004.840947.
- [107] Q. Tang, A. Shen, W. Li, P. Luo, M. Chen, and X. He, "Multiple-Positions-Coupled Sampling Method for PMSM Three-Phase Current Reconstruction With a Single Current Sensor," *IEEE Trans. Power Electron.*, vol. 35, no. 1, pp. 699–708, Jan. 2020, doi: 10.1109/TPEL.2019.2913684.
- [108] H. Kim and T. M. Jahns, "Phase Current Reconstruction for AC Motor Drives using a DC-link Single Current Sensor and Measurement Voltage Vectors," in *2005 IEEE 36th Power Electronics Specialists Conference*, Jun. 2005, pp. 1346–1352. doi: 10.1109/PESC.2005.1581804.
- [109] J.-I. Ha, "Voltage Injection Method for Three-Phase Current Reconstruction in PWM Inverters Using a Single Sensor," *IEEE Trans. Power Electron.*, vol. 24, no. 3, pp. 767–775, Mar. 2009, doi: 10.1109/TPEL.2008.2009451.
- [110] Y.-S. Lai, Y.-K. Lin, and C.-W. Chen, "New Hybrid Pulsewidth Modulation Technique to Reduce Current Distortion and Extend Current Reconstruction Range for a Three-Phase Inverter Using Only DC-link Sensor," *IEEE Trans. Power Electron.*, vol. 28, no. 3, pp. 1331–1337, Mar. 2013, doi: 10.1109/TPEL.2012.2207406.
- [111] S.-C. Yang, "Saliency-Based Position Estimation of Permanent-Magnet Synchronous Machines Using Square-Wave Voltage Injection With a Single Current Sensor," *IEEE Trans. Ind. Appl.*, vol. 51, no. 2, pp. 1561–1571, Mar. 2015, doi: 10.1109/TIA.2014.2358796.

- [112] J. Lu, Y. Hu, X. Zhang, Z. Wang, J. Liu, and C. Gan, "High-Frequency Voltage Injection Sensorless Control Technique for IPMSMs Fed by a Three-Phase Four-Switch Inverter With a Single Current Sensor," *IEEEASME Trans. Mechatron.*, vol. 23, no. 2, pp. 758–768, Apr. 2018, doi: 10.1109/TMECH.2018.2803772.
- [113] E. Un and A. M. Hava, "A Near-State PWM Method With Reduced Switching Losses and Reduced Common-Mode Voltage for Three-Phase Voltage Source Inverters," *IEEE Trans. Ind. Appl.*, vol. 45, no. 2, pp. 782–793, Mar. 2009, doi: 10.1109/TIA.2009.2013580.
- [114] K. Sun, Q. Wei, L. Huang, and K. Matsuse, "An Overmodulation Method for PWM-Inverter-Fed IPMSM Drive With Single Current Sensor," *IEEE Trans. Ind. Electron.*, vol. 57, no. 10, pp. 3395–3404, Oct. 2010, doi: 10.1109/TIE.2009.2038336.
- [115] Y. Gu, F. Ni, D. Yang, and H. Liu, "Switching-State Phase Shift Method for Three-Phase Current Reconstruction With a Single DC-Link Current Sensor," *IEEE Trans. Ind. Electron.*, vol. 58, no. 11, pp. 5186–5194, Nov. 2011, doi: 10.1109/TIE.2011.2123854.
- [116] H. Lu, X. Cheng, W. Qu, S. Sheng, Y. Li, and Z. Wang, "A Three-Phase Current Reconstruction Technique Using Single DC Current Sensor Based on TSPWM," *IEEE Trans. Power Electron.*, vol. 29, no. 3, pp. 1542–1550, Mar. 2014, doi: 10.1109/TPEL.2013.2266408.
- [117] X. Li, S. Dusmez, B. Akin, and K. Rajashekara, "A new SVPWM for phase currents reconstruction of three-phase three-level T-type converters," in *2015 IEEE Applied Power Electronics Conference and Exposition (APEC)*, Mar. 2015, pp. 1582–1588. doi: 10.1109/APEC.2015.7104558.
- [118] J. Lu, X. Zhang, Y. Hu, J. Liu, C. Gan, and Z. Wang, "Independent Phase Current Reconstruction Strategy for IPMSM Sensorless Control Without Using Null Switching States," *IEEE Trans. Ind. Electron.*, vol. 65, no. 6, pp. 4492–4502, Jun. 2018, doi: 10.1109/TIE.2017.2767542.
- [119] S. Song, Z. Xia, G. Fang, R. Ma, and W. Liu, "Phase Current Reconstruction and Control of Three-Phase Switched Reluctance Machine With Modular Power Converter Using Single DC-Link Current Sensor," *IEEE Trans. Power Electron.*, vol. 33, no. 10, pp. 8637–8649, Oct. 2018, doi: 10.1109/TPEL.2017.2782562.
- [120] B. Saritha and P. A. Janakiraman, "Sinusoidal Three-Phase Current Reconstruction and Control Using a DC-Link Current Sensor and a Curve-Fitting Observer," *IEEE Trans. Ind. Electron.*, vol. 54, no. 5, pp. 2657–2664, Oct. 2007, doi: 10.1109/TIE.2007.899842.
- [121] J.-I. Ha, "Current Prediction in Vector-Controlled PWM Inverters Using Single DC-Link Current Sensor," *IEEE Trans. Ind. Electron.*, vol. 57, no. 2, pp. 716–726, Feb. 2010, doi: 10.1109/TIE.2009.2028361.
- [122] B. Hafez, A. S. Abdel-Khalik, A. M. Massoud, S. Ahmed, and R. D. Lorenz, "Single-Sensor-Based Three-Phase Permanent-Magnet Synchronous Motor Drive System With Luenberger Observers for Motor Line Current Reconstruction," *IEEE Trans. Ind. Appl.*, vol. 50, no. 4, pp. 2602–2613, Jul. 2014, doi: 10.1109/TIA.2013.2296625.
- [123] C. Gan, J. Wu, S. Yang, Y. Hu, and W. Cao, "Wavelet Packet Decomposition-Based Fault Diagnosis Scheme for SRM Drives With a Single Current Sensor," *IEEE Trans. Energy Convers.*, vol. 31, no. 1, pp. 303–313, Mar. 2016, doi: 10.1109/TEC.2015.2476835.
- [124] J.-H. Im and R.-Y. Kim, "Improved Saliency-Based Position Sensorless Control of Interior Permanent-Magnet Synchronous Machines With Single DC-Link Current Sensor Using Current Prediction Method," *IEEE Trans. Ind. Electron.*, vol. 65, no. 7, pp. 5335–5343, Jul. 2018, doi: 10.1109/TIE.2017.2777382.
- [125] Y.-H. Cho, A. Koran, H. Miwa, B. York, and J.-S. Lai, "An active current reconstruction and balancing strategy with DC-link current sensing for a multi-phase coupled-inductor

- converter,” in *2010 IEEE Energy Conversion Congress and Exposition*, Sep. 2010, pp. 3414–3419. doi: 10.1109/ECCE.2010.5618316.
- [126] Y. Cho, T. LaBella, and J.-S. Lai, “A Three-Phase Current Reconstruction Strategy With Online Current Offset Compensation Using a Single Current Sensor,” *IEEE Trans. Ind. Electron.*, vol. 59, no. 7, pp. 2924–2933, Jul. 2012, doi: 10.1109/TIE.2011.2171177.
- [127] Y. Xu, H. Yan, J. Zou, B. Wang, and Y. Li, “Zero Voltage Vector Sampling Method for PMSM Three-Phase Current Reconstruction Using Single Current Sensor,” *IEEE Trans. Power Electron.*, vol. 32, no. 5, pp. 3797–3807, May 2017, doi: 10.1109/TPEL.2016.2588141.
- [128] W. Jiang and B. Fahimi, “Current reconstruction techniques for survivable three phase PWM converters,” in *2009 IEEE International Electric Machines and Drives Conference*, May 2009, pp. 888–893. doi: 10.1109/IEMDC.2009.5075309.
- [129] A. Consoli, S. Musumeci, A. Raciti, and A. Testa, “Sensorless vector and speed control of brushless motor drives,” *IEEE Trans. Ind. Electron.*, vol. 41, no. 1, pp. 91–96, Feb. 1994, doi: 10.1109/41.281613.
- [130] J.-L. Shi, T.-H. Liu, and Y.-C. Chang, “Position Control of an Interior Permanent-Magnet Synchronous Motor Without Using a Shaft Position Sensor,” *IEEE Trans. Ind. Electron.*, vol. 54, no. 4, pp. 1989–2000, Jun. 2007, doi: 10.1109/TIE.2007.895137.
- [131] D. C. Hanselman, “Resolver signal requirements for high accuracy resolver-to-digital conversion,” *IEEE Trans. Ind. Electron.*, vol. 37, no. 6, pp. 556–561, Dec. 1990, doi: 10.1109/41.103461.
- [132] H. S. Mok, S. H. Kim, and Y. H. Cho, “Reduction of PMSM torque ripple caused by resolver position error,” p. 4.
- [133] Y.-H. Kwon, S.-H. Hwang, J.-M. Kim, and J.-W. Ahn, “Compensation of amplitude imbalance of resolver signal for PMSM drives,” in *2009 IEEE 6th International Power Electronics and Motion Control Conference*, May 2009, pp. 1827–1831. doi: 10.1109/IPEMC.2009.5157691.
- [134] W. Lee, J.-J. Moon, W.-S. Im, J.-H. Park, and J.-M. Kim, “Classification and Compensation of DC Offset Error and Scale Error in Resolver Signals,” *J. Power Electron.*, vol. 16, no. 3, pp. 1190–1199, May 2016, doi: 10.6113/JPE.2016.16.3.1190.
- [135] S.-H. Hwang, H.-J. Kim, J.-M. Kim, L. Liu, and H. Li, “Compensation of Amplitude Imbalance and Imperfect Quadrature in Resolver Signals for PMSM Drives,” *IEEE Trans. Ind. Appl.*, vol. 47, no. 1, pp. 134–143, Jan. 2011, doi: 10.1109/TIA.2010.2091477.
- [136] J.-J. Moon, H.-J. Heo, W.-S. Im, and J.-M. Kim, “Classification and compensation of amplitude imbalance and imperfect quadrature in resolver signals,” in *2014 16th European Conference on Power Electronics and Applications*, Aug. 2014, pp. 1–7. doi: 10.1109/EPE.2014.6911048.
- [137] Y.-H. Ou-Yang and K.-T. Tang, “An Energy-Efficient SAR ADC With Event-Triggered Error Correction,” *IEEE Trans. Circuits Syst. II Express Briefs*, vol. 66, no. 5, pp. 723–727, May 2019, doi: 10.1109/TCSII.2019.2909294.
- [138] “Understanding and minimising ADC conversion errors,” p. 42.
- [139] “ADC Offset Error - Developer Help.” Accessed: Aug. 20, 2022. [Online]. Available: <https://microchipdeveloper.com/adc:adc-offset-error>
- [140] P. Pickering, “Behind the ADC Veil: Demystifying Common DC Specifications,” *Electronic Design*. Accessed: Feb. 27, 2023. [Online]. Available: <https://www.electronicdesign.com/technologies/analog/article/21807150/behind-the-adc-veil-demystifying-common-dc-specifications>

- [141] "Precision improvement techniques for the A/D converter of the STM8 microcontroller," p. 22.
- [142] "How to Increase the Analog-to-Digital Converter Accuracy in an Application," p. 20.
- [143] "Understanding and minimising ADC conversion errors.pdf." Accessed: Aug. 20, 2022. [Online]. Available: https://www.st.com/resource/en/application_note/cd00004444-understanding-and-minimising-adc-conversion-errors-stmicroelectronics.pdf
- [144] A. Aggarwal, I. M. Allafi, E. G. Strangas, and J. S. Agapiou, "Off-Line Detection of Static Eccentricity of PMSM Robust to Machine Operating Temperature and Rotor Position Misalignment Using Incremental Inductance Approach," *IEEE Trans. Transp. Electrification*, vol. 7, no. 1, pp. 161–169, Mar. 2021, doi: 10.1109/TTE.2020.3006016.
- [145] Z. Tang and B. Akin, "A New LMS Algorithm Based Deadtime Compensation Method for PMSM FOC Drives," *IEEE Trans. Ind. Appl.*, vol. 54, no. 6, pp. 6472–6484, Nov. 2018, doi: 10.1109/TIA.2018.2853045.
- [146] H. Yan, Y. Xu, W. Zhao, H. Zhang, and C. Gerada, "DC Drift Error Mitigation Method for Three-Phase Current Reconstruction With Single Hall Current Sensor," *IEEE Trans. Magn.*, vol. 55, no. 2, pp. 1–4, Feb. 2019, doi: 10.1109/TMAG.2018.2869837.
- [147] Q. Ni *et al.*, "A New Position and Speed Estimation Scheme for Position Control of PMSM Drives Using Low-Resolution Position Sensors," *IEEE Trans. Ind. Appl.*, vol. 55, no. 4, pp. 3747–3758, Jul. 2019, doi: 10.1109/TIA.2019.2904934.
- [148] S. Xie and A. Theuvsen, "A 10 Bit 5 MS/s Column SAR ADC With Digital Error Correction for CMOS Image Sensors," *IEEE Trans. Circuits Syst. II Express Briefs*, vol. 67, no. 6, pp. 984–988, Jun. 2020, doi: 10.1109/TCSII.2019.2928204.
- [149] A. Consoli, G. Scarcella, and A. Testa, "Industry application of zero-speed sensorless control techniques for PM synchronous motors," *IEEE Trans. Ind. Appl.*, vol. 37, no. 2, pp. 513–521, Mar. 2001, doi: 10.1109/28.913716.
- [150] O. Wallmark, L. Harnefors, and O. Carlson, "An improved speed and position estimator for salient permanent-magnet synchronous motors," *IEEE Trans. Ind. Electron.*, vol. 52, no. 1, pp. 255–262, Feb. 2005, doi: 10.1109/TIE.2004.841088.
- [151] Y. Park and S.-K. Sul, "Sensorless control method for PMSM based on frequency-adaptive disturbance observer," in *2013 IEEE Energy Conversion Congress and Exposition*, Sep. 2013, pp. 3807–3814. doi: 10.1109/ECCE.2013.6647205.
- [152] S. Shinnaka, "New 'D-State-Observer'-based vector control for sensorless drive of permanent-magnet synchronous motors," *IEEE Trans. Ind. Appl.*, vol. 41, no. 3, pp. 825–833, May 2005, doi: 10.1109/TIA.2005.847282.
- [153] Y. Zhao, W. Qiao, and L. Wu, "An Adaptive Quasi-Sliding-Mode Rotor Position Observer-Based Sensorless Control for Interior Permanent Magnet Synchronous Machines," *IEEE Trans. Power Electron.*, vol. 28, no. 12, pp. 5618–5629, Dec. 2013, doi: 10.1109/TPEL.2013.2246871.
- [154] X. Zhang, L. Sun, K. Zhao, and L. Sun, "Nonlinear Speed Control for PMSM System Using Sliding-Mode Control and Disturbance Compensation Techniques," *IEEE Trans. Power Electron.*, vol. 28, no. 3, pp. 1358–1365, Mar. 2013, doi: 10.1109/TPEL.2012.2206610.
- [155] Z. Yin, C. Zhao, Y.-R. Zhong, and J. Liu, "Research on Robust Performance of Speed-Sensorless Vector Control for the Induction Motor Using an Interfacing Multiple-Model Extended Kalman Filter," *IEEE Trans. Power Electron.*, vol. 29, no. 6, pp. 3011–3019, Jun. 2014, doi: 10.1109/TPEL.2013.2272091.
- [156] Z. Q. Zhu, Y. F. Shi, and D. Howe, "Rotor position sensing in brushless ac motors with self-shielding magnets using linear Hall sensors," *J. Appl. Phys.*, vol. 99, no. 8, p. 08R313, Apr. 2006, doi: 10.1063/1.2172178.

- [157] J. Hu, J. Zou, F. Xu, Y. Li, and Y. Fu, "An Improved PMSM Rotor Position Sensor Based on Linear Hall Sensors," *IEEE Trans. Magn.*, vol. 48, no. 11, pp. 3591–3594, Nov. 2012, doi: 10.1109/TMAG.2012.2202279.
- [158] R. Wegener, F. Senicar, C. Junge, and S. Soter, "Low Cost Position Sensor for Permanent Magnet Linear Drive," in *2007 7th International Conference on Power Electronics and Drive Systems*, Nov. 2007, pp. 1367–1371. doi: 10.1109/PEDS.2007.4487882.
- [159] X. Song, J. Fang, B. Han, and S. Zheng, "Adaptive Compensation Method for High-Speed Surface PMSM Sensorless Drives of EMF-Based Position Estimation Error," *IEEE Trans. Power Electron.*, vol. 31, no. 2, pp. 1438–1449, Feb. 2016, doi: 10.1109/TPEL.2015.2423319.
- [160] Y. Park and S.-K. Sul, "A Novel Method Utilizing Trapezoidal Voltage to Compensate for Inverter Nonlinearity," *IEEE Trans. Power Electron.*, vol. 27, no. 12, pp. 4837–4846, Dec. 2012, doi: 10.1109/TPEL.2012.2192451.
- [161] Y. Inoue, K. Yamada, S. Morimoto, and M. Sanada, "Effectiveness of Voltage Error Compensation and Parameter Identification for Model-Based Sensorless Control of IPMSM," *IEEE Trans. Ind. Appl.*, vol. 45, no. 1, pp. 213–221, Jan. 2009, doi: 10.1109/TIA.2008.2009617.
- [162] T. Hoshino and J. Itoh, "Output Voltage Correction for a Voltage Source Type Inverter of an Induction Motor Drive," *IEEE Trans. Power Electron.*, vol. 25, no. 9, pp. 2440–2449, Sep. 2010, doi: 10.1109/TPEL.2010.2049031.
- [163] S.-H. Jung, H. Kobayashi, S. Doki, and S. Okuma, "An improvement of sensorless control performance by a mathematical modelling method of spatial harmonics for a SynRM," in *The 2010 International Power Electronics Conference - ECCE ASIA -*, Jun. 2010, pp. 2010–2015. doi: 10.1109/IPEC.2010.5543555.
- [164] G. Wang, H. Zhan, G. Zhang, X. Gui, and D. Xu, "Adaptive Compensation Method of Position Estimation Harmonic Error for EMF-Based Observer in Sensorless IPMSM Drives," *IEEE Trans. Power Electron.*, vol. 29, no. 6, pp. 3055–3064, Jun. 2014, doi: 10.1109/TPEL.2013.2276613.
- [165] G. Wang, G. Zhang, and D. Xu, *Position Sensorless Control Techniques for Permanent Magnet Synchronous Machine Drives*. Springer Nature, 2019.
- [166] G. Zhang, G. Wang, D. Xu, and N. Zhao, "ADALINE-Network-Based PLL for Position Sensorless Interior Permanent Magnet Synchronous Motor Drives," *IEEE Trans. Power Electron.*, vol. 31, no. 2, pp. 1450–1460, Feb. 2016, doi: 10.1109/TPEL.2015.2424256.
- [167] P. Rodríguez, A. Luna, R. S. Muñoz-Aguilar, I. Etxeberria-Otadui, R. Teodorescu, and F. Blaabjerg, "A Stationary Reference Frame Grid Synchronization System for Three-Phase Grid-Connected Power Converters Under Adverse Grid Conditions," *IEEE Trans. Power Electron.*, vol. 27, no. 1, pp. 99–112, Jan. 2012, doi: 10.1109/TPEL.2011.2159242.
- [168] G. Zhang, G. Wang, D. Xu, R. Ni, and C. Jia, "Multiple-AVF Cross-Feedback-Network-Based Position Error Harmonic Fluctuation Elimination for Sensorless IPMSM Drives," *IEEE Trans. Ind. Electron.*, vol. 63, no. 2, pp. 821–831, Feb. 2016, doi: 10.1109/TIE.2015.2492939.
- [169] D. Raca, P. Garcia, D. Dí. Reigosa, F. Briz, and R. D. Lorenz, "Carrier-Signal Selection for Sensorless Control of PM Synchronous Machines at Zero and Very Low Speeds," *IEEE Trans. Ind. Appl.*, vol. 46, no. 1, pp. 167–178, Jan. 2010, doi: 10.1109/TIA.2009.2036551.
- [170] A. Ravikumar Setty, S. Wekhande, and K. Chatterjee, "Comparison of high frequency signal injection techniques for rotor position estimation at low speed to standstill of

- PMSM,” in *2012 IEEE 5th India International Conference on Power Electronics (IICPE)*, Dec. 2012, pp. 1–6. doi: 10.1109/IICPE.2012.6450521.
- [171] J.-H. Jang, J.-I. Ha, M. Ohto, K. Ide, and S.-K. Sul, “Analysis of permanent-magnet machine for sensorless control based on high-frequency signal injection,” *IEEE Trans. Ind. Appl.*, vol. 40, no. 6, pp. 1595–1604, Nov. 2004, doi: 10.1109/TIA.2004.836222.
 - [172] E. Robeischl and M. Schroedl, “Optimized INFORM measurement sequence for sensorless PM synchronous motor drives with respect to minimum current distortion,” *IEEE Trans. Ind. Appl.*, vol. 40, no. 2, pp. 591–598, Mar. 2004, doi: 10.1109/TIA.2004.824510.
 - [173] Q. Tang, A. Shen, X. Luo, and J. Xu, “PMSM Sensorless Control by Injecting HF Pulsating Carrier Signal Into ABC Frame,” *IEEE Trans. Power Electron.*, vol. 32, no. 5, pp. 3767–3776, May 2017, doi: 10.1109/TPEL.2016.2583787.
 - [174] J.-Y. Chai, Y.-H. Ho, Y.-C. Chang, and C.-M. Liaw, “On Acoustic-Noise-Reduction Control Using Random Switching Technique for Switch-Mode Rectifiers in PMSM Drive,” *IEEE Trans. Ind. Electron.*, vol. 55, no. 3, pp. 1295–1309, Mar. 2008, doi: 10.1109/TIE.2007.909759.
 - [175] G. Wang, L. Yang, G. Zhang, X. Zhang, and D. Xu, “Comparative Investigation of Pseudorandom High-Frequency Signal Injection Schemes for Sensorless IPMSM Drives,” *IEEE Trans. Power Electron.*, vol. 32, no. 3, pp. 2123–2132, Mar. 2017, doi: 10.1109/TPEL.2016.2569418.
 - [176] D. Q. Guan, M. X. Bui, D. Xiao, and M. F. Rahman, “Evaluation of an FPGA current derivative measurement system for the fundamental PWM excitation sensorless method for IPMSM,” in *2016 IEEE 2nd Annual Southern Power Electronics Conference (SPEC)*, Dec. 2016, pp. 1–6. doi: 10.1109/SPEC.2016.7846196.
 - [177] Y. Shibano and H. Kubota, “Pole Position Estimation Method of IPMSM at Low Speed without High Frequency Components Injection,” in *2009 Twenty-Fourth Annual IEEE Applied Power Electronics Conference and Exposition*, Feb. 2009, pp. 233–239. doi: 10.1109/APEC.2009.4802661.
 - [178] Y. Hosogaya and H. Kubota, “Position estimating method of IPMSM at low speed region using dq-axis current derivative without high frequency component,” in *2013 IEEE 10th International Conference on Power Electronics and Drive Systems (PEDS)*, Apr. 2013, pp. 1306–1311. doi: 10.1109/PEDS.2013.6527221.
 - [179] Y. Hosogaya and H. Kubota, “Sensorless control method of IPMSM with current derivative information of q-axis without high frequency component injection at low speed region,” in *2013 IEEE ECCE Asia Downunder*, Jun. 2013, pp. 799–803. doi: 10.1109/ECCE-Asia.2013.6579194.
 - [180] Y. Hosogaya and H. Kubota, “Flux position estimation method of IPMSM by controlling current derivative at zero voltage vector,” in *2010 International Conference on Electrical Machines and Systems*, Oct. 2010, pp. 894–899.
 - [181] M. N. Uddin, T. S. Radwan, and M. A. Rahman, “Fuzzy-logic-controller-based cost-effective four-switch three-phase inverter-fed IPM synchronous motor drive system,” *IEEE Trans. Ind. Appl.*, vol. 42, no. 1, pp. 21–30, Jan. 2006, doi: 10.1109/TIA.2005.861277.
 - [182] E. Z. M. Salem, A. Haitham Z., A.-G. Saad F., and M. M. Elkholy, “Open gate fault diagnosis and tolerant for voltage source inverter fed speed sensorless induction motor drive,” *Int. J. Electron.*, vol. 107, no. 11, pp. 1754–1772, Nov. 2020, doi: 10.1080/00207217.2020.1756434.

- [183] J. Kim, J. Hong, and K. Nam, "A Current Distortion Compensation Scheme for Four-Switch Inverters," *IEEE Trans. Power Electron.*, vol. 24, no. 4, pp. 1032–1040, Apr. 2009, doi: 10.1109/TPEL.2008.2011552.
- [184] Z. Zeng, W. Zheng, R. Zhao, C. Zhu, and Q. Yuan, "Modeling, Modulation, and Control of the Three-Phase Four-Switch PWM Rectifier Under Balanced Voltage," *IEEE Trans. Power Electron.*, vol. 31, no. 7, pp. 4892–4905, Jul. 2016, doi: 10.1109/TPEL.2015.2480539.
- [185] F. Blaabjerg, D. O. Neacsu, and J. K. Pedersen, "Adaptive SVM to compensate DC-link voltage ripple for four-switch three-phase voltage-source inverters," *IEEE Trans. Power Electron.*, vol. 14, no. 4, pp. 743–752, Jul. 1999, doi: 10.1109/63.774214.
- [186] M. B. de Rossiter Correa, C. B. Jacobina, E. R. C. da Silva, and A. M. N. Lima, "A General PWM Strategy for Four-Switch Three-Phase Inverters," *IEEE Trans. Power Electron.*, vol. 21, no. 6, pp. 1618–1627, Nov. 2006, doi: 10.1109/TPEL.2006.882964.
- [187] C. Zhu, Z. Zeng, and R. Zhao, "Adaptive suppression method for DC-link voltage offset in three-phase four-switch inverter-fed PMSM drives," *Electron. Lett.*, vol. 52, no. 17, pp. 1442–1444, 2016, doi: 10.1049/el.2016.2048.
- [188] K. Ni, Y. Hu, Y. Liu, and C. Gan, "Overview on fault-tolerant four-switch three-phase voltage source converters," *Chin. J. Electr. Eng.*, vol. 3, no. 2, pp. 87–101, Sep. 2017, doi: 10.23919/CJEE.2017.8048415.
- [189] Z. Zeng, W. Zheng, R. Zhao, C. Zhu, and Q. Yuan, "The Comprehensive Design and Optimization of the Post-Fault Grid-Connected Three-Phase PWM Rectifier," *IEEE Trans. Ind. Electron.*, vol. 63, no. 3, pp. 1629–1642, Mar. 2016, doi: 10.1109/TIE.2015.2494854.
- [190] Z. Zeng, W. Zheng, and R. Zhao, "Space-Vector-Based Hybrid PWM Strategy for Reduced DC-Link Capacitor Current Stress in the Postfault Grid-Connected Three-Phase Rectifier," *IEEE Trans. Ind. Electron.*, vol. 63, no. 8, pp. 4989–5000, Aug. 2016, doi: 10.1109/TIE.2016.2547367.
- [191] N. M. A. Freire and A. J. M. Cardoso, "A Fault-Tolerant Direct Controlled PMSG Drive for Wind Energy Conversion Systems," *IEEE Trans. Ind. Electron.*, vol. 61, no. 2, pp. 821–834, Feb. 2014, doi: 10.1109/TIE.2013.2251734.
- [192] W. Wang, A. Luo, X. Xu, L. Fang, T. M. Chau, and Z. Li, "Space vector pulse-width modulation algorithm and DC-side voltage control strategy of three-phase four-switch active power filters," *IET Power Electron.*, vol. 6, no. 1, pp. 125–135, 2013, doi: 10.1049/iet-pel.2012.0391.
- [193] D. Zhou, J. Zhao, and Y. Liu, "Predictive Torque Control Scheme for Three-Phase Four-Switch Inverter-Fed Induction Motor Drives With DC-Link Voltages Offset Suppression," *IEEE Trans. Power Electron.*, vol. 30, no. 6, pp. 3309–3318, Jun. 2015, doi: 10.1109/TPEL.2014.2338395.
- [194] Z. Zeng, C. Zhu, X. Jin, W. Shi, and R. Zhao, "Hybrid Space Vector Modulation Strategy for Torque Ripple Minimization in Three-Phase Four-Switch Inverter-Fed PMSM Drives," *IEEE Trans. Ind. Electron.*, vol. 64, no. 3, pp. 2122–2134, Mar. 2017, doi: 10.1109/TIE.2016.2625768.
- [195] C. Zhu, Z. Zeng, and R. Zhao, "Comprehensive Analysis and Reduction of Torque Ripples in Three-Phase Four-Switch Inverter-Fed PMSM Drives Using Space Vector Pulse-Width Modulation," *IEEE Trans. Power Electron.*, vol. 32, no. 7, pp. 5411–5424, Jul. 2017, doi: 10.1109/TPEL.2016.2605160.
- [196] C. Xia, J. Zhao, Y. Yan, and T. Shi, "A Novel Direct Torque Control of Matrix Converter-Fed PMSM Drives Using Duty Cycle Control for Torque Ripple Reduction," *IEEE*

- Trans. Ind. Electron.*, vol. 61, no. 6, pp. 2700–2713, Jun. 2014, doi: 10.1109/TIE.2013.2276039.
- [197] Y.-S. Lai and J.-H. Chen, “A new approach to direct torque control of induction motor drives for constant inverter switching frequency and torque ripple reduction,” *IEEE Trans. Energy Convers.*, vol. 16, no. 3, pp. 220–227, Sep. 2001, doi: 10.1109/60.937200.
 - [198] J. Lang, C. Tong, Y. Zheng, J. Bai, and P. Zheng, “Decoupled Dead-Time Compensation Method Using Revised-Resonant Control-Based Disturbance Observer in PMSM Drives,” *IEEE Trans. Power Electron.*, vol. 40, no. 1, pp. 340–350, Jan. 2025, doi: 10.1109/TPEL.2024.3458406.
 - [199] J. Ye, M. Wang, S. Cui, C. Zhang, and L. Li, “Enhanced Deadtime Compensation Strategy Combining Current Prediction and Drive Pulse Rectification for Three-Phase VSI,” *IEEE J. Emerg. Sel. Top. Ind. Electron.*, vol. 6, no. 2, pp. 827–836, Apr. 2025, doi: 10.1109/JESTIE.2024.3512437.
 - [200] J.-H. Lee and S.-K. Sul, “Inverter Nonlinearity Compensation Through Deadtime Effect Estimation,” *IEEE Trans. Power Electron.*, vol. 36, no. 9, pp. 10684–10694, Sep. 2021, doi: 10.1109/TPEL.2021.3061285.
 - [201] M. G. Joksimovic, E. Levi, and S. N. Vukosavic, “Near-Complete Suppression of Harmonic Currents in SPMSMs Caused by Back EMF and Dead Time,” *IEEE Trans. Ind. Electron.*, vol. 70, no. 5, pp. 4472–4484, May 2023, doi: 10.1109/TIE.2022.3189068.
 - [202] R. Heckman and C. Quinn, “The Growth of Wide Bandgap Technology in Industrial Power Conversion,” *IEEE Power Electron. Mag.*, vol. 11, no. 4, pp. 54–60, Dec. 2024, doi: 10.1109/MPEL.2024.3492294.
 - [203] X. Sun, Z. Su, G. Lei, and M. Yao, “Robust Predictive Cascaded Speed and Current Control for PMSM Drives Considering Parameter Variations,” *IEEE Trans. Ind. Electron.*, vol. 71, no. 9, pp. 10235–10245, Sep. 2024, doi: 10.1109/TIE.2023.3337498.
 - [204] X. Wen *et al.*, “Research on Sensitivity of Slot-Pole Combination to Unbalanced Magnetic Pull Induced by Rotor Eccentricity,” *IEEE Trans. Ind. Appl.*, vol. 60, no. 4, pp. 6186–6196, Jul. 2024, doi: 10.1109/TIA.2024.3398615.
 - [205] H. Zhan, W. Liu, Z. Lyu, S. Niu, L. Wu, and K. T. Chau, “Eccentricity Fault Diagnosis in Multimodule Permanent Magnet Synchronous Machines Based on Zero-Sequence Voltage Component,” *IEEE Trans. Ind. Electron.*, vol. 72, no. 12, pp. 12332–12342, Dec. 2025, doi: 10.1109/TIE.2025.3574542.
 - [206] F. Ding, X. Liu, and C. Fu, “Adaptive Barrier Function Based Predefined-Time Sliding Mode Control for PMSM With Disturbance Suppression,” *IEEE Trans. Ind. Electron.*, vol. 73, no. 6, pp. 8208–8219, Jun. 2026, doi: 10.1109/TIE.2025.3647875.
 - [207] X. Fu and J. Xiong, “Multielement Disturbance Observer for Separately Estimating Periodic and Nonperiodic Disturbances in PMSM Control Systems,” *IEEE Trans. Power Electron.*, vol. 41, no. 3, pp. 3388–3398, Mar. 2026, doi: 10.1109/TPEL.2025.3605206.
 - [208] W. Kirchgässner, O. Wallscheid, and J. Böcker, “Data-Driven Permanent Magnet Temperature Estimation in Synchronous Motors With Supervised Machine Learning: A Benchmark,” *IEEE Trans. Energy Convers.*, vol. 36, no. 3, pp. 2059–2067, Sep. 2021, doi: 10.1109/TEC.2021.3052546.
 - [209] X. Wu *et al.*, “Virtual Viable Sampling Timing via CPWM-DPWM Switching for Current Measurement Errors Calibration in PMSM Drive,” *IEEE Trans. Ind. Electron.*, vol. 71, no. 9, pp. 10277–10287, Sep. 2024, doi: 10.1109/TIE.2023.3335319.
 - [210] X. Feng, B. Wang, Z. Wang, and W. Hua, “Investigation and Diagnosis of Current Sensor Fault in Permanent Magnet Machine Drives,” *IEEE Trans. Ind. Electron.*, vol. 72, no. 2, pp. 1261–1270, Feb. 2025, doi: 10.1109/TIE.2024.3417988.

- [211] R. K. Dissanayake and S. S. Kuruppu, "Extremum-Seeking Approach for Real-Time Self-Healing of Position Sensor Offset Error in PMSMs," *IEEE Trans. Transp. Electrification*, vol. 11, no. 1, pp. 3125–3136, Feb. 2025, doi: 10.1109/TTE.2024.3435349.
- [212] B. Chen, K. Wang, and Y. Le, "High-Precision Position Error Correction Method for the PMSM Based on Low-Order Harmonic Suppression," *IEEE Trans. Power Electron.*, vol. 36, no. 4, pp. 4500–4512, Apr. 2021, doi: 10.1109/TPEL.2020.3019886.
- [213] M. Hu, W. Liu, S. Niu, X. Yuan, and K. T. Chau, "Digital Current Control for Permanent Magnet Synchronous Machine Drives With Fractional-Step Computation Delay," *IEEE Trans. Transp. Electrification*, vol. 12, no. 1, pp. 641–651, Feb. 2026, doi: 10.1109/TTE.2025.3619989.
- [214] Y. Wei, Y. Wei, Y. Sun, H. Qi, X. Guo, and M. Li, "A Smith Structure-Based Delay Compensation Method for Model Predictive Current Control of PMSM System," *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 10, no. 4, pp. 4090–4101, Aug. 2022, doi: 10.1109/JESTPE.2021.3137299.
- [215] H. Lee, M. L. Woldesemayat, and K. Nam, "Zero Torque Control for EV Coasting Considering Cross-Coupling Inductance," *IEEE Trans. Ind. Electron.*, vol. 64, no. 8, pp. 6096–6104, Aug. 2017, doi: 10.1109/TIE.2017.2681973.
- [216] F. Aghili, "Optimal Feedback Linearization Control of Interior PM Synchronous Motors Subject to Time-Varying Operation Conditions Minimizing Power Loss," *IEEE Trans. Ind. Electron.*, vol. 65, no. 7, pp. 5414–5421, Jul. 2018, doi: 10.1109/TIE.2017.2784348.
- [217] Z. Lin, X. Ruan, H. Zhang, and L. Wu, "A Generalized Real-Time Computation Method With Dual-Sampling Mode to Eliminate the Computation Delay in Digitally Controlled Inverters," *IEEE Trans. Power Electron.*, vol. 37, no. 5, pp. 5186–5195, May 2022, doi: 10.1109/TPEL.2021.3129069.
- [218] S. Buso and P. Mattavelli, *Digital Control in Power Electronics*. in Synthesis Lectures on Power Electronics. Cham: Springer International Publishing, 2015. doi: 10.1007/978-3-031-02499-3.
- [219] D. G. Holmes, T. A. Lipo, B. P. McGrath, and W. Y. Kong, "Optimized Design of Stationary Frame Three Phase AC Current Regulators," *IEEE Trans. Power Electron.*, vol. 24, no. 11, pp. 2417–2426, Nov. 2009, doi: 10.1109/TPEL.2009.2029548.
- [220] Y. Zhang, D. Xu, J. Liu, S. Gao, and W. Xu, "Performance Improvement of Model-Predictive Current Control of Permanent Magnet Synchronous Motor Drives," *IEEE Trans. Ind. Appl.*, vol. 53, no. 4, pp. 3683–3695, Jul. 2017, doi: 10.1109/TIA.2017.2690998.
- [221] X. Zhang, X. Yu, and G. Zhang, "Adaptive Model Predictive Current Control for PMSM Drives Based on Bayesian Inference," *IEEE Trans. Power Electron.*, vol. 40, no. 6, pp. 8490–8502, Jun. 2025, doi: 10.1109/TPEL.2025.3535907.
- [222] J. Wang, H. Yang, Y. Liu, and J. Rodríguez, "Low-Cost Multistep FCS-MPCC for PMSM Drives Using a DC Link Single Current Sensor," *IEEE Trans. Power Electron.*, vol. 37, no. 9, pp. 11034–11044, Sep. 2022, doi: 10.1109/TPEL.2022.3167557.
- [223] T. Li, X. Sun, M. Yao, D. Guo, and Y. Sun, "Improved Finite Control Set Model Predictive Current Control for Permanent Magnet Synchronous Motor With Sliding Mode Observer," *IEEE Trans. Transp. Electrification*, vol. 10, no. 1, pp. 699–710, Mar. 2024, doi: 10.1109/TTE.2023.3293510.
- [224] X. Zhang, Y. Zhang, and J. Zhang, "Flux-Weakening Strategy for PMSM Finite-Control-Set Model Predictive Control System Utilizing Closed Loop of Expected Fundamental Voltage," *IEEE Trans. Ind. Electron.*, vol. 73, no. 1, pp. 319–330, Jan. 2026, doi: 10.1109/TIE.2025.3598192.

- [225] F. Wang, Z. Li, X. Yu, D. Ke, F. Grimm, and R. Kennel, "High Performance Model Predictive Control for PMSM System Using Bayesian Ascent and Gaussian Process," *IEEE Trans. Energy Convers.*, vol. 39, no. 2, pp. 851–861, Jun. 2024, doi: 10.1109/TEC.2023.3338456.
- [226] A. Kiselev, G. R. Catuogno, A. Kuznietsov, and R. Leidhold, "Finite-Control-Set MPC for Open-Phase Fault-Tolerant Control of PM Synchronous Motor Drives," *IEEE Trans. Ind. Electron.*, vol. 67, no. 6, pp. 4444–4452, Jun. 2020, doi: 10.1109/TIE.2019.2931285.
- [227] P. Kanjiya, V. Khadkikar, and M. S. El Moursi, "Adaptive Low-Pass Filter Based DC Offset Removal Technique for Three-Phase PLLs," *IEEE Trans. Ind. Electron.*, vol. 65, no. 11, pp. 9025–9029, Nov. 2018, doi: 10.1109/TIE.2018.2814015.
- [228] Y. Bai *et al.*, "An Adaptive-Frequency Harmonic Suppression Strategy Based on Vector Reconstruction for Current Measurement Error of PMSM Drives," *IEEE Trans. Power Electron.*, vol. 38, no. 1, pp. 34–40, Jan. 2023, doi: 10.1109/TPEL.2022.3200708.
- [229] Y. Han, C. Gong, Z. Ma, C. Liu, W. Li, and G. Chen, "Precise Cumulative Error Calibration With Delay Effects Rejected for Incremental Encoders Used in High-Speed PMSMs," *IEEE Trans. Ind. Electron.*, vol. 69, no. 9, pp. 9667–9672, Sep. 2022, doi: 10.1109/TIE.2021.3116576.
- [230] Y. Zhang and H. Yang, "Model-Predictive Flux Control of Induction Motor Drives With Switching Instant Optimization," *IEEE Trans. Energy Convers.*, vol. 30, no. 3, pp. 1113–1122, Sep. 2015, doi: 10.1109/TEC.2015.2423692.
- [231] X. Zhang and B. Hou, "Double Vectors Model Predictive Torque Control Without Weighting Factor Based on Voltage Tracking Error," *IEEE Trans. Power Electron.*, vol. 33, no. 3, pp. 2368–2380, Mar. 2018, doi: 10.1109/TPEL.2017.2691776.
- [232] C. Gong, L. Ding, Y. Li, and J. Li, "Improved Sensorless FCS-MPCC With Current Pre-Estimation-Based Delay Compensation Integrated for PMSMs Over High-Speed Range," *IEEE Trans. Ind. Appl.*, vol. 59, no. 6, pp. 6756–6765, Nov. 2023, doi: 10.1109/TIA.2023.3298307.
- [233] F. Tinazzi, P. G. Carlet, S. Bolognani, and M. Zigliotto, "Motor Parameter-Free Predictive Current Control of Synchronous Motors by Recursive Least-Square Self-Commissioning Model," *IEEE Trans. Ind. Electron.*, vol. 67, no. 11, pp. 9093–9100, Nov. 2020, doi: 10.1109/TIE.2019.2956407.
- [234] B. Luo, X. Yang, and Y. Zhou, "Model-Free Predictive Current Control of Permanent Magnet Synchronous Motor Based on Estimation of Current Variations," *IEEE Trans. Ind. Electron.*, vol. 71, no. 8, pp. 8395–8405, Aug. 2024, doi: 10.1109/TIE.2023.3331133.
- [235] M. Siami, D. A. Khaburi, A. Abbaszadeh, and J. Rodriguez, "Robustness Improvement of Predictive Current Control Using Prediction Error Correction for Permanent-Magnet Synchronous Machines," *IEEE Trans. Ind. Electron.*, vol. 63, no. 6, pp. 3458–3466, Jun. 2016, doi: 10.1109/TIE.2016.2521734.
- [236] X. Li, S. Cheng, D. Wang, Z. Ji, Y. Hu, and Y. Lv, "A Nonintrusive Current Sensor Gain Tuning Method for Interior Permanent Magnet Synchronous Motor Drives Using Controlled Short-Circuit Tests," *IEEE Trans. Transp. Electrification*, vol. 8, no. 1, pp. 1278–1288, Mar. 2022, doi: 10.1109/TTE.2021.3118013.
- [237] S. Suzuki and M. Yoshida, "Elevator control apparatus with compensation for current sensor offset voltage," US5407027A, Apr. 18, 1995 Accessed: Jan. 22, 2025. [Online]. Available: <https://patents.google.com/patent/US5407027A/en>

- [238] L. F. da S. Coelho, L. Lovisollo, and M. P. Tcheou, "Adaptive Filtering With Reduced Computational Complexity Using SOPOT Arithmetic," *IEEE Trans. Circuits Syst. Regul. Pap.*, vol. 69, no. 2, pp. 746–756, Feb. 2022, doi: 10.1109/TCSI.2021.3119285.
- [239] J. S., S. K. Yadav, and N. V. George, "Adaptive Low-Rank DOA Estimation Using Complex Kronecker Product Decomposition," *IEEE Trans. Veh. Technol.*, vol. 73, no. 7, pp. 10726–10731, Jul. 2024, doi: 10.1109/TVT.2024.3363017.
- [240] W. Li, Z. Wang, J. Hu, J. Du, and W. Sheng, "Kernel Adaptive Filtering Over Complex Networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 4339–4346, Mar. 2024, doi: 10.1109/TNNLS.2022.3199679.
- [241] Y. Wang, Z. Li, J. Qiu, S. Zhou, H. Li, and Z. Zhang, "Robust Encoderless Control for PMSM Drives via a Revised Unscented Kalman Filter," *IEEE Trans. Ind. Electron.*, vol. 73, no. 2, pp. 1837–1848, Feb. 2026, doi: 10.1109/TIE.2025.3607947.
- [242] W. Li *et al.*, "Simplified Hybrid Adaptive Kalman Filter With Fading-Triggered Resonance Mechanism for PMSM Speed-Sensorless Control," *IEEE Trans. Circuits Syst. II Express Briefs*, vol. 72, no. 11, pp. 1740–1744, Nov. 2025, doi: 10.1109/TCSII.2025.3612703.
- [243] T. Chen, R. Zhao, J. Chen, and Z. Zhang, "Data-Driven Active Disturbance Rejection Control of Plant-Protection Unmanned Ground Vehicle Prototype: A Fuzzy Indirect Iterative Learning Approach," *IEEECAA J. Autom. Sin.*, vol. 11, no. 8, pp. 1892–1894, Aug. 2024, doi: 10.1109/JAS.2023.124158.
- [244] Y. Wang, S. Fang, J. Hu, and D. Huang, "A Novel Active Disturbance Rejection Control of PMSM Based on Deep Reinforcement Learning for More Electric Aircraft," *IEEE Trans. Energy Convers.*, vol. 38, no. 2, pp. 1461–1470, Jun. 2023, doi: 10.1109/TEC.2023.3235927.
- [245] K. Zhang, M. Fan, Y. Yang, Z. Zhu, C. Garcia, and J. Rodriguez, "An Improved Adaptive Selected Harmonic Elimination Algorithm for Current Measurement Error Correction of PMSMs," *IEEE Trans. Power Electron.*, vol. 36, no. 11, pp. 13128–13138, Nov. 2021, doi: 10.1109/TPEL.2021.3076993.
- [246] M. Tian, B. Wang, Y. Yu, Q. Dong, and D. Xu, "Adaptive Active Disturbance Rejection Control for Uncertain Current Ripples Suppression of PMSM Drives," *IEEE Trans. Ind. Electron.*, vol. 71, no. 3, pp. 2320–2331, Mar. 2024, doi: 10.1109/TIE.2023.3265045.
- [247] J. Liu, C. Gong, Z. Han, and H. Yu, "IPMSM Model Predictive Control in Flux-Weakening Operation Using an Improved Algorithm," *IEEE Trans. Ind. Electron.*, vol. 65, no. 12, pp. 9378–9387, Dec. 2018, doi: 10.1109/TIE.2018.2818640.
- [248] J. Rodriguez, R. M. Kennel, J. R. Espinoza, M. Trincado, C. A. Silva, and C. A. Rojas, "High-Performance Control Strategies for Electrical Drives: An Experimental Assessment," *IEEE Trans. Ind. Electron.*, vol. 59, no. 2, pp. 812–820, Feb. 2012, doi: 10.1109/TIE.2011.2158778.
- [249] J. Hong and R. Cao, "Adaptive Selective Harmonic Elimination Model Predictive Control for Three-Level T-Type Inverter," *IEEE Access*, vol. 8, pp. 157983–157994, 2020, doi: 10.1109/ACCESS.2020.3020216.
- [250] P. Du, B. Wang, and D. Xu, "Steady and Transient State Performance Balancing Strategy of Adaptive Complex-Vector Filter in PMSM Sensorless Control," *IEEE Trans. Ind. Electron.*, vol. 72, no. 9, pp. 8915–8928, Sep. 2025, doi: 10.1109/TIE.2025.3541294.
- [251] J. S., S. K. Yadav, M. L. N. S. Karthik, and N. V. George, "Fourier Domain Gradient Descent Total Least Square/Fourth Algorithm for Efficient Adaptive Direction of Arrival Estimation," *IEEE Trans. Veh. Technol.*, vol. 75, no. 2, pp. 2426–2438, Feb. 2026, doi: 10.1109/TVT.2025.3599310.

- [252] C. Lian, F. Xiao, J. Liu, and S. Gao, "Parameter and VSI Nonlinearity Hybrid Estimation for PMSM Drives Based on Recursive Least Square," *IEEE Trans. Transp. Electrification*, vol. 9, no. 2, pp. 2195–2206, Jun. 2023, doi: 10.1109/TTE.2022.3206606.
- [253] B. Jalal, X. Yang, X. Wu, T. Long, and T. K. Sarkar, "Efficient Direction-of-Arrival Estimation Method Based on Variable-Step-Size LMS Algorithm," *IEEE Antennas Wirel. Propag. Lett.*, vol. 18, no. 8, pp. 1576–1580, Aug. 2019, doi: 10.1109/LAWP.2019.2923700.
- [254] Q. Liu, X. Huo, K.-Z. Liu, and H. Zhao, "A Parallelized Input Matching LMS Adaptive Filter for the Rejection of Spatially Cyclic Disturbances," *IEEE Trans. Ind. Electron.*, vol. 70, no. 10, pp. 10536–10545, Oct. 2023, doi: 10.1109/TIE.2022.3224161.
- [255] P. Monsurrò and A. Trifiletti, "Faster, Stabler, and Simpler—A Recursive-Least-Squares Algorithm Exploiting the Frisch–Waugh–Lovell Theorem," *IEEE Trans. Circuits Syst. II Express Briefs*, vol. 64, no. 3, pp. 344–348, Mar. 2017, doi: 10.1109/TCSII.2016.2565725.
- [256] P. Chen, Y. Luo, L. Zhang, X. Wang, and Y. Chen, "PMSM Speed Ripple Suppression Due to Current Measurement Error Using Quasi-Fractional Resonant-Normalized Extended State Observer," *IEEE Trans. Control Syst. Technol.*, vol. 33, no. 2, pp. 554–565, Mar. 2025, doi: 10.1109/TCST.2024.3492805.
- [257] H. Dan *et al.*, "Current Measurement Error Compensation Based on Current Ripple Component Decoupling for PMSM Drives," *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 13, no. 2, pp. 1699–1709, Apr. 2025, doi: 10.1109/JESTPE.2024.3468388.
- [258] P. Song, Y. Wang, E. Ma, L. Wu, T. Wang, and H. Li, "Current Measurement Error Compensation Based on Modified Multiple Complex-Coefficient Filters in PMSM Drives," *IEEE Trans. Power Electron.*, vol. 40, no. 3, pp. 4067–4079, Mar. 2025, doi: 10.1109/TPEL.2024.3507110.
- [259] S. Cai, J. L. Kirtley, and C. H. T. Lee, "Critical Review of Direct-Drive Electrical Machine Systems for Electric and Hybrid Electric Vehicles," *IEEE Trans. Energy Convers.*, vol. 37, no. 4, pp. 2657–2668, Dec. 2022, doi: 10.1109/TEC.2022.3197351.
- [260] L. Quan, W. Fan, X. Zhu, L. Xu, and H. Liu, "Flux-Oriented Design and Analysis of a Hybrid Rotor Pole Interior Permanent Magnet Motor for In-Wheel Direct Drive," *IEEE Trans. Transp. Electrification*, pp. 1–1, 2024, doi: 10.1109/TTE.2023.3332048.
- [261] Y. Yu, Y. Pei, F. Chai, and M. Doppelbauer, "Analysis of Back EMF Harmonics Influenced by Slot–Pole Combinations in Permanent Magnet Vernier In-Wheel Motors," *IEEE Trans. Ind. Electron.*, vol. 70, no. 5, pp. 4461–4471, May 2023, doi: 10.1109/TIE.2022.3189065.
- [262] Q. Zhang *et al.*, "A Novel Error-Injected Solution for Compensation of Current Measurement Errors in PMSM Drive," *IEEE Trans. Ind. Electron.*, vol. 70, no. 5, pp. 4608–4619, May 2023, doi: 10.1109/TIE.2022.3186343.
- [263] W. Hu *et al.*, "Hierarchical Fault-Isolated Observer Framework for Incipient Current-Sensor Fault Diagnosis and Sensorless Control in SPMSM Drives," *IEEE Trans. Power Electron.*, pp. 1–16, 2026, doi: 10.1109/TPEL.2026.3697744.
- [264] X. Yu, X. Wu, T. Wu, D. Yang, Z. Lei, and S. Huang, "An FTSMO-Based Current Measurement Offset Error Compensation Method in SPMSM Drives," *IEEE Trans. Ind. Electron.*, vol. 72, no. 7, pp. 6840–6851, Jul. 2025, doi: 10.1109/TIE.2024.3519570.
- [265] R. Mei, D. Zhou, X. Liu, J. Zou, and Z. Shen, "Time-Series Disturbance Observer-Based Multi-Rate Predictive Control of High-Switching-Frequency Power Converters," *IEEE Trans. Power Electron.*, pp. 1–14, 2026, doi: 10.1109/TPEL.2026.3691939.

- [266] X. Zhang and Y. Cao, "A Simple Motor-Parameter-Free Model Predictive Current Control for PMSM Drive," *IEEE Trans. Ind. Electron.*, vol. 72, no. 4, pp. 3292–3302, Apr. 2025, doi: 10.1109/TIE.2024.3447750.
- [267] X. Zhang, S. Fang, and H. Zhang, "Predictive Current Error Compensation Based Strong Robust Model Predictive Control for PMSM Drive Systems," *IEEE Trans. Ind. Electron.*, vol. 71, no. 12, pp. 15280–15289, Dec. 2024, doi: 10.1109/TIE.2024.3379650.
- [268] C. Attaianesi, M. D'Arpino, M. D. Monaco, and L. P. D. Noia, "Isolation, Detection and Estimation of Current Sensors Faults in PMSM Drives Based on Current Signature Modeling," *IEEE Trans. Energy Convers.*, vol. 40, no. 1, pp. 653–664, Mar. 2025, doi: 10.1109/TEC.2024.3448369.
- [269] H. Choi, J.-I. Ha, and K. Lee, "Ultra-Low Inductance PMSM Drive Using a DC Current Sensor," *IEEE Trans. Ind. Electron.*, vol. 71, no. 6, pp. 5597–5607, Jun. 2024, doi: 10.1109/TIE.2023.3288203.
- [270] J. Ye *et al.*, "Discrete-Time Improved Equivalent-Input-Disturbance Control with Dynamic Decoupled Adaptive Damping Regulator for PMSM Current Enhancement," *IEEE Trans. Transp. Electrification*, pp. 1–1, 2026, doi: 10.1109/TTE.2026.3674504.
- [271] X. Zhang *et al.*, "Improved Data-Driven Finite Control-Set Predictive Control for Dual Three-Phase PMSMs with Low Current Ripple," *IEEE Trans. Ind. Appl.*, pp. 1–13, 2026, doi: 10.1109/TIA.2026.3683642.
- [272] W. Wang *et al.*, "New Three-Phase Current Reconstruction for PMSM Drive With Hybrid Space Vector Pulsewidth Modulation Technique," *IEEE Trans. Power Electron.*, vol. 36, no. 1, pp. 662–673, Jan. 2021, doi: 10.1109/TPEL.2020.2997986.
- [273] Y. Zuo *et al.*, "A Novel Current Measurement Offset Error Compensation Method Based on the Adaptive Extended State Observer for IPMSM Drives," *IEEE Trans. Ind. Electron.*, vol. 71, no. 4, pp. 3371–3382, Apr. 2024, doi: 10.1109/TIE.2023.3277084.
- [274] A. Holczer, F. D. Freijedo, and R. Bojoi, "Optimal High-Frequency Injection Minimizing High-Frequency Torque Ripple for Sensorless Control of Electric Vehicle IPM Traction Motors," *IEEE Trans. Ind. Electron.*, vol. 72, no. 5, pp. 4424–4435, May 2025, doi: 10.1109/TIE.2024.3454189.
- [275] M. Naderian, G. A. Markadeh, M. Karimi-Ghartemani, and M. Mojiri, "Improved Sensorless Control Strategy for IPMSM Using an ePLL Approach With High-Frequency Injection," *IEEE Trans. Ind. Electron.*, vol. 71, no. 3, pp. 2231–2241, Mar. 2024, doi: 10.1109/TIE.2023.3270528.
- [276] P. Zhang, S. Wang, and Y. Li, "Sensorless Control of IPMSM in Zero- and Low-Speed Regions Using Dual Random High-Frequency Square-Wave Voltage Injection to Reduce Audible Noise," *IEEE Trans. Ind. Electron.*, vol. 71, no. 10, pp. 11864–11875, Oct. 2024, doi: 10.1109/TIE.2024.3360609.
- [277] Y. Chen, Z. Q. Zhu, X. Wu, H. Yang, L. Yang, and C. Liu, "Novel Anti-Rotating D-Axis Signal Injection-Based Inductance Asymmetry Compensation for High Frequency Signal Injection Sensorless Control of IPMSMs," *IEEE Trans. Ind. Electron.*, pp. 1–12, 2025, doi: 10.1109/TIE.2025.3553181.
- [278] J. Yim, S. You, Y. Lee, and W. Kim, "Chattering Attenuation Disturbance Observer for Sliding Mode Control: Application to Permanent Magnet Synchronous Motors," *IEEE Trans. Ind. Electron.*, vol. 70, no. 5, pp. 5161–5170, May 2023, doi: 10.1109/TIE.2022.3189074.
- [279] D. Wang and X. Liu, "Sensorless Control of PMSM With Improved Adaptive Super-Twisting Sliding Mode Observer and IST-QSG," *IEEE Trans. Transp. Electrification*, vol. 11, no. 1, pp. 721–731, Feb. 2025, doi: 10.1109/TTE.2024.3395318.

- [280] C. Song, W. Hu, J. Zhang, C. Zhao, and X. Sun, "A Gain-Adaptive High-Order Terminal Sliding Mode Observer Under SPMSM Sensorless Control," *IEEE Trans. Power Electron.*, vol. 40, no. 5, pp. 6555–6565, May 2025, doi: 10.1109/TPEL.2025.3525550.
- [281] Z. Cheng, L. Li, X. Liu, X. Bai, and J. Liu, "Sensorless Control Based on Discrete Fractional-Order Terminal Sliding Mode Observer for High-Speed PMSM With LCL Filter," *IEEE Trans. Power Electron.*, vol. 40, no. 1, pp. 1654–1668, Jan. 2025, doi: 10.1109/TPEL.2024.3443401.
- [282] R. Cao, N. Jiang, and M. Lu, "Sensorless Control of Linear Flux-Switching Permanent Magnet Motor Based on Extended Kalman Filter," *IEEE Trans. Ind. Electron.*, vol. 67, no. 7, pp. 5971–5979, Jul. 2020, doi: 10.1109/TIE.2019.2950865.
- [283] F. Xiang, K. Yu, C. Chen, and S. Li, "Sensorless Control of PMSM Drives Using Octant Newton-Raphson Method and Reduced-Order EKF Considering Speed Reversal and Noise," *IEEE Trans. Power Electron.*, pp. 1–11, 2025, doi: 10.1109/TPEL.2025.3556963.
- [284] X. Li and R. Kennel, "General Formulation of Kalman-Filter-Based Online Parameter Identification Methods for VSI-Fed PMSM," *IEEE Trans. Ind. Electron.*, vol. 68, no. 4, pp. 2856–2864, Apr. 2021, doi: 10.1109/TIE.2020.2977568.
- [285] Z. Yang, Z. Yan, Y. Lu, W. Wang, L. Yu, and Y. Geng, "Double DOF Strategy for Continuous-Wave Pulse Generator Based on Extended Kalman Filter and Adaptive Linear Active Disturbance Rejection Control," *IEEE Trans. Power Electron.*, vol. 37, no. 2, pp. 1382–1393, Feb. 2022, doi: 10.1109/TPEL.2021.3105392.
- [286] P. Koothu Kesavan, U. Subramaniam, and D. J. Almkhles, "Reduced Switch Inverter-Fed Sensorless PMSM Drive With Multistage MRAS Speed Estimator Based on Stator Flux and Electromagnetic Torque," *IEEE Trans. Transp. Electrification*, vol. 10, no. 2, pp. 2620–2631, Jun. 2024, doi: 10.1109/TTE.2023.3304194.
- [287] D. Chen, J. Wang, and L. Zhou, "Adaptive Second-Order Active-Flux Observer for Sensorless Control of PMSMs With MRAS-Based VSI Nonlinearity Compensation," *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 11, no. 3, pp. 3076–3086, Jun. 2023, doi: 10.1109/JESTPE.2023.3253578.
- [288] N. Jiang, R. Cao, W. Sun, D. Chen, and K. Wang, "MRAS-Based Sensorless Control of PMSM Drives Using Extended State Observer in Shaftless Rim-Driven Thruster System," *IEEE Trans. Transp. Electrification*, vol. 11, no. 2, pp. 6038–6047, Apr. 2025, doi: 10.1109/TTE.2024.3496715.
- [289] L. Yuan, K. Han, C. Zhang, X. Zhu, and Y. Ding, "Comparative Analysis of Full-Order SMO and STM-MRAS in SPMSM Sensorless Drive System," *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 12, no. 3, pp. 2592–2603, Jun. 2024, doi: 10.1109/JESTPE.2024.3378806.
- [290] B. Yu *et al.*, "A Compensation Strategy of Flux Linkage Observer in SPMSM Sensorless Drives Based on Linear Extended State Observer," *IEEE Trans. Energy Convers.*, vol. 37, no. 2, pp. 824–831, Jun. 2022, doi: 10.1109/TEC.2021.3114283.
- [291] J. Liu and Y. Zhang, "Performance Improvement of Nonlinear Flux Observer for Sensorless Control of PMSM," *IEEE Trans. Ind. Electron.*, vol. 70, no. 12, pp. 12014–12023, Dec. 2023, doi: 10.1109/TIE.2023.3236112.
- [292] Q. Tang, D. Chen, and X. He, "Integration of Improved Flux Linkage Observer and I–f Starting Method for Wide-Speed-Range Sensorless SPMSM Drives," *IEEE Trans. Power Electron.*, vol. 35, no. 8, pp. 8374–8383, Aug. 2020, doi: 10.1109/TPEL.2019.2963208.
- [293] A. T. Woldegiorgis, X. Ge, Y. Zuo, H. Wang, and M. Hassan, "Sensorless Control of Interior Permanent Magnet Synchronous Motor Drives Considering Resistance and

- Permanent Magnet Flux Linkage Variation,” *IEEE Trans. Ind. Electron.*, vol. 70, no. 8, pp. 7716–7730, Aug. 2023, doi: 10.1109/TIE.2022.3224152.
- [294] W. Zine, Z. Makni, E. Monmasson, L. Idkhajine, and B. Condamin, “Interests and Limits of Machine Learning-Based Neural Networks for Rotor Position Estimation in EV Traction Drives,” *IEEE Trans. Ind. Inform.*, vol. 14, no. 5, pp. 1942–1951, May 2018, doi: 10.1109/TII.2017.2765398.
- [295] L. N. Tan, T. P. Cong, and D. P. Cong, “Neural Network Observers and Sensorless Robust Optimal Control for Partially Unknown PMSM With Disturbances and Saturating Voltages,” *IEEE Trans. Power Electron.*, vol. 36, no. 10, pp. 12045–12056, Oct. 2021, doi: 10.1109/TPEL.2021.3071465.
- [296] J. Lu, Y. Hu, J. Wang, Y. Song, Y. Su, and J. Liu, “Synergistic Correction of Current Sampling Errors in Dual-Motor Powered Electric Powertrain for High Power Electric Vehicles,” *IEEE Trans. Ind. Electron.*, vol. 69, no. 1, pp. 225–235, Jan. 2022, doi: 10.1109/TIE.2021.3053890.
- [297] S. Foti, A. Testa, S. De Caro, T. Scimone, and M. Pulvirenti, “Rotor Flux Position Correction and Parameters Estimation on Sensorless Multiple Induction Motors Drives,” *IEEE Trans. Ind. Appl.*, vol. 55, no. 4, pp. 3759–3769, Jul. 2019, doi: 10.1109/TIA.2019.2906862.
- [298] C. Yang, F. Meng, H. Zhang, J. Zhao, H. Wang, and L. Zhou, “Optimal Coordinated Control for Speed Tracking and Torque Synchronization of Rigidly Connected Dual-Motor Systems,” *IEEEASME Trans. Mechatron.*, vol. 28, no. 5, pp. 2609–2620, Oct. 2023, doi: 10.1109/TMECH.2023.3242663.
- [299] Y. Song, J. Lu, Y. Hu, X. Wu, and G. Wang, “Fast Calibration With Raw Data Verification for Current Measurement of Dual-PMSM Drives,” *IEEE Trans. Ind. Electron.*, vol. 71, no. 7, pp. 6875–6885, Jul. 2024, doi: 10.1109/TIE.2023.3312432.
- [300] Y. Wang, Y. Feng, X. Zhang, and J. Liang, “A New Reaching Law for Antidisturbance Sliding-Mode Control of PMSM Speed Regulation System,” *IEEE Trans. Power Electron.*, vol. 35, no. 4, pp. 4117–4126, Apr. 2020, doi: 10.1109/TPEL.2019.2933613.
- [301] T. H. Nguyen, T. T. Nguyen, V. Q. Nguyen, K. M. Le, H. N. Tran, and J. W. Jeon, “An Adaptive Sliding-Mode Controller With a Modified Reduced-Order Proportional Integral Observer for Speed Regulation of a Permanent Magnet Synchronous Motor,” *IEEE Trans. Ind. Electron.*, vol. 69, no. 7, pp. 7181–7191, Jul. 2022, doi: 10.1109/TIE.2021.3102427.
- [302] X. Zhu *et al.*, “An Improved Sliding Model Observer Sensorless Control for PMSM Based on Fuzzy Logic Controller and DSOGI-FLL,” *IEEE Trans. Transp. Electrification*, vol. 11, no. 1, pp. 823–834, Feb. 2025, doi: 10.1109/TTE.2024.3396732.
- [303] H. Li, Z. Wang, C. Wen, and X. Wang, “Sensorless Control of Surface-Mounted Permanent Magnet Synchronous Motor Drives Using Nonlinear Optimization,” *IEEE Trans. Power Electron.*, vol. 34, no. 9, pp. 8930–8943, Sep. 2019, doi: 10.1109/TPEL.2018.2885552.
- [304] T. Vo-Duy, T.-M. Doan, B.-H. Nguyễn, and J. P. F. Trovão, “Optimal Energy Management System of Dual-Motor Electric Vehicles With Longitudinal Dynamic Characteristic Consideration,” *IEEE Trans. Veh. Technol.*, vol. 74, no. 2, pp. 2559–2571, Feb. 2025, doi: 10.1109/TVT.2023.3285906.
- [305] N. V. Vantagodi *et al.*, “Design of a Scaled Roller-Rig Test Bench for Anti-Slip Control Development for Railway Traction,” *IEEE Trans. Veh. Technol.*, vol. 72, no. 4, pp. 4320–4331, Apr. 2023, doi: 10.1109/TVT.2022.3226607.
- [306] X. Ding, Z. Wang, and L. Zhang, “Hybrid Control-Based Acceleration Slip Regulation for Four-Wheel-Independent-Actuated Electric Vehicles,” *IEEE Trans. Transp.*

Electrification, vol. 7, no. 3, pp. 1976–1989, Sep. 2021, doi: 10.1109/TTE.2020.3048405.

- [307] Z. He, Q. Shi, Y. Wei, B. Gao, B. Zhu, and L. He, “A Model Predictive Control Approach With Slip Ratio Estimation for Electric Motor Antilock Braking of Battery Electric Vehicle,” *IEEE Trans. Ind. Electron.*, vol. 69, no. 9, pp. 9225–9234, Sep. 2022, doi: 10.1109/TIE.2021.3112966.

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