

Received: xxx Accepted: xxx Published: xxx.

DOI: [10.30473/coam.2026.78140.1418](https://doi.org/10.30473/coam.2026.78140.1418)

Volume xxx, Issue xxx, p.p. 1-32: xxx

Research Article



Open Access

Control and Optimization in Applied Mathematics - COAM

Hierarchical Harmonic-Injection and Nonlinear Model Predictive Control for Fault-Tolerant Operation of High-Power Seven-Phase Induction Motor Drives

Zargham Heydari¹✉, Hamed Gorginpour², Nariman Heidari³

¹Department of Electrical Engineering, Khorm.C., Islamic Azad University, Khormoj, Iran

²Faculty of Intelligent Systems Engineering and Data Science, Persian Gulf University, Bushehr, Iran

³Department of Computer Engineering, Bu.C., Islamic Azad University, Bushehr, Iran

✉ Correspondence:

Zargham Heydari

E-mail:

zargham.hidari@iau.ac.ir

How to Cite

Heydari, Z., Gorginpour, H., Heidari, N. (2027). "Hierarchical harmonic-injection and nonlinear model predictive control for fault-tolerant operation of high-power seven-phase induction motor drives". *Control and Optimization in Applied Mathematics*, X(x), 1-32. <https://doi.org/10.30473/coam.2026.78140.1418>

Abstract. High-power multiphase induction motors are attractive for safety-critical and power-intensive applications because of their inherent advantages, including superior fault tolerance, lower per-phase power requirements, and reduced torque pulsation. Under open-phase faults, however, the loss of phase symmetry couples the fundamental and harmonic subspaces, increasing torque ripple and current distortion. This paper develops a hierarchical control framework for a high-power seven-phase induction motor that combines online harmonic-reference optimization with enhanced nonlinear model predictive control (ENMPC). The upper layer estimates the machine state and slowly varying electrical parameters using an Extended Kalman Filter (EKF) and weighted recursive least squares (WRLS), and determines reference components in the third- and fifth-harmonic subspaces. The lower layer directly regulates the fundamental and harmonic current components subject to voltage, current, and terminal-state constraints. An explicit fault-constrained state-space representation is derived for one open phase and two adjacent open phases, and a terminal-set Lyapunov argument is given for nominal recursive feasibility and asymptotic closed-loop stability. MATLAB/Simulink simulations of the 1-MW plant consider a healthy interval, a single-phase open fault at 4 s, and an adjacent two-phase open fault at 8 s. For the reported cases, the compensated hierarchical controller maintains 5.76 kN·m and 4.68 kN·m of effective torque under the single- and two-phase fault conditions, respectively, while the corresponding torque-ripple factors are 4.8% and 8.5%. These results support the proposed architecture as a fault-tolerant control strategy while also defining the present study as simulation-based and motivating hardware-in-the-loop and experimental validation.

Keywords. Seven-phase induction motor, Open-phase fault, Harmonic injection, Nonlinear model predictive control, Fault-tolerant control.

MSC. 49J15; 93B45; 93C10.

<https://mathco.journals.pnu.ac.ir>

©2026 by the authors. Licensee PNU, Tehran, Iran. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution 4.0 International (CC BY4.0) (<http://creativecommons.org/licenses/by/4.0>)

1 Introduction

Multiphase induction drives are established candidates for applications in which power splitting, continuity of operation, and low torque pulsation are important. Their additional electrical degrees of freedom permit current redistribution and post-fault control without adding redundant machine phases [1, 5, 12, 20], while recent reviews also emphasize the broader role of multiphase motor-drive systems in high-power and electrified powertrains [6]. For the present study, the plant is the 1-MW, four-pole seven-phase induction motor design reported by Heidari et al. [11]; that prior work addresses electromagnetic-thermal machine design, whereas the contribution developed here concerns the faulted dynamic model and its hierarchical control. Open-phase faults, however, destroy phase symmetry and generate negative-sequence and harmonic magnetomotive-force components, which can increase torque ripple, mechanical vibration, thermal stress, and loss [18, 21]. Post-fault operation must therefore account explicitly for both the torque-producing and secondary current subspaces.

A review of the literature reveals that control strategies for multiphase motors under fault conditions have primarily evolved around two main axes: modification of transformation matrices, and harmonic current injection.

1.1 Strategies Based on Transformation Modification and Vector Control

Transformation-based fault-tolerant control exploits vector-space decomposition to redistribute the current references after a phase loss. Barrero and Duran [1, 5] summarize the modeling basis and the use of additional subspaces in multiphase drives, while the more recent surveys of Yepes et al. [20, 21] distinguish reconfiguration-based and natural fault-tolerant strategies for open-circuit faults. In experimentally validated multiphase induction drives, field-oriented control can be formulated so that acceptable post-fault operation is retained without a complete controller reconstruction [10]. These approaches are effective for preserving average torque, but suppressing the fault-induced coupling between harmonic planes remains a separate control objective.

1.2 Strategies Based on Harmonic Injection

Harmonic-current injection addresses torque pulsation more directly by shaping current components in the secondary subspaces. Liu et al. [13] showed that the coupling of spatial harmonic fields is a principal source of post-fault ripple and optimized current-space-vector components for one- and two-phase open faults in a five-phase induction motor. For seven-phase induction

machines, Yang et al. [18] proposed a harmonic-injection fault-tolerant strategy that explicitly decouples harmonic planes and reduces torque ripple, while their subsequent SVPWM formulation [19] reconstructs admissible voltage vectors under a single-phase open-circuit fault. These studies establish that the secondary subspaces should be controlled deliberately rather than treated as parasitic components.

A further development is online optimization of post-fault current references. Yepes et al. [22] formulated a general online current-harmonic generation method that is applicable to healthy and open-phase operation and minimizes stator copper loss over the torque range. This line of work is directly relevant to the present upper-layer optimizer because it demonstrates that harmonic references can be adapted online without relying on a fixed lookup table. The present paper differs by coupling the harmonic-reference layer to a constrained nonlinear predictive controller that tracks the fundamental, third-, and fifth-harmonic subspaces simultaneously.

1.3 Model Predictive Controllers (MPC) in Multiphase Systems

In multiphase motor drives, model predictive control has emerged as a leading control paradigm because it can evaluate multivariable objectives and hard constraints within a single optimization problem. González-Prieto et al. [8] introduced virtual-voltage-vector MPC for six-phase induction-motor drives, and subsequently assessed its open-phase behavior and natural fault-tolerant capability [9]. Related fault-tolerant predictive-current strategies have been demonstrated in six-phase PMSM drives [7, 15] and in nine-phase drives [17]. These studies provide the closest predictive-control benchmark family for the present work: they regulate converter voltage vectors or current components under faults, whereas the proposed ENMPC uses an explicit fault-coupled nonlinear state model and receives optimized third- and fifth-harmonic references from a separate adaptive layer.

A competing recent direction is model-free predictive control. Chen et al. [3] reported natural fault-tolerant model-free predictive flux control for a five-phase PMSM under arbitrary open-circuit faults, thereby reducing dependence on a fixed parameterized plant model. This trend is important because it trades explicit model structure for online disturbance estimation. The present study follows the complementary model-based route: the fault-induced subspace coupling is retained explicitly, so that state, input, harmonic-current, and terminal constraints can be handled in a single nonlinear predictive formulation.

Table 1 shows that the closest alternatives solve different parts of the same post-fault problem: virtual-vector MPC emphasizes converter-vector selection, online harmonic methods emphasize current-reference generation, and model-free predictive control emphasizes parameter insensitivity. The present contribution is positioned at their intersection by retaining an explicit seven-phase fault model while updating harmonic references online and enforcing nonlinear

Table 1: Methodological comparison with representative fault-tolerant predictive and harmonic-reference approaches

Study	Machine / fault condition	Control principle and verified strength	Boundary relative to the present work
González-Prieto et al. [8] (2018)	Six-phase IM; predictive drive control	Virtual-voltage-vector MPC; suppresses secondary-subspace currents while retaining flux/torque control; experimental	Healthy-operation architecture; no open-phase case in this paper and no adaptive harmonic-reference layer
González-Prieto et al. [9] (2020)	Six-phase drive; open-phase faults	Natural fault-tolerant virtual-vector MPC for post-fault operation; experimental	Finite/virtual-vector formulation; no EKF/WRLS layer or simultaneous third-/fifth-harmonic reference optimization
Wang et al. [17] (2022)	Nine-phase motor; open-phase faults	Enhanced natural fault-tolerant MPCC corrects virtual-vector shifting; experimental	Nine-phase finite-control-set structure; no terminal-set ENMPC or online harmonic-parameter estimator
Yepes et al. [22] (2023)	Multiphase IM; healthy and open-phase operation	Online harmonic-current generation increases torque capability while minimizing stator copper loss; experimental six-phase IM	Optimizes current references but does not impose nonlinear predictive state, voltage, or terminal constraints
Chen et al. [3] (2025)	Five-phase PMSM; arbitrary open-circuit faults	Model-free predictive flux control using an ultra-local model and disturbance estimation; experimental	Five-phase PMSM and model-free formulation; no explicit fault-coupled seven-phase induction-motor model
Present study	Seven-phase IM; one open phase and two adjacent open phases	Two-rate EKF/WRLS harmonic-reference optimization plus constrained ENMPC; explicit fault projections and terminal-set stability	Integrated model-based harmonic-reference generation and nonlinear predictive tracking; numerical validation of the specified 1-MW scenarios

predictive constraints. Cross-paper numerical rankings are intentionally avoided because the machines, ratings, fault sets, sampling rates, and experimental platforms are not common across these studies.

1.4 Research Gaps

The systematic review of recent literature (2022–2025) reveals several fundamental and practical research gaps hindering the achievement of optimal performance in high-power seven-phase induction motors under open-phase fault conditions.

Gap 1 (*Online harmonic optimization*). Existing harmonic-injection and online current-reference methods demonstrate substantial post-fault benefits [18, 13, 22], but they do not jointly provide the present combination of online third- and fifth-harmonic reference adaptation and constrained nonlinear predictive tracking for a seven-phase induction motor. The unresolved issue is therefore not the existence of harmonic injection itself, but the coordination of the reference-optimization and predictive-control layers.

Gap 2 (*Integrated MPC framework*). Virtual-vector and finite-control-set predictive controllers are well established for multiphase drives [8, 9, 7, 15, 17], including open-phase operation. The remaining gap addressed here is direct, simultaneous tracking of the fundamental, third-harmonic, and fifth-harmonic current subspaces in a nonlinear MPC formulation whose harmonic references are generated online.

Gap 3 (*Fault-coupled modeling and stability*). Open-phase faults impose algebraic phase-current constraints that couple otherwise orthogonal subspaces. The present work therefore requires an explicit fault-constrained state model rather than a qualitative statement that the state matrices change. In addition, controller stability must follow standard nonlinear MPC conditions based on a terminal cost and an invariant terminal set [4, 14], not the distributed-computing notion of self-stabilization.

Gap 4 (*Hierarchical control for high power*). The surveyed literature treats harmonic-reference optimization and predictive converter control largely as separate design problems. The contribution pursued here is a two-rate hierarchical architecture in which a slower parameter/reference layer supplies harmonic commands while a faster ENMPC enforces current and voltage constraints. For the 1-MW case, Section 3.5 characterizes the online burden through the explicit 12–60-variable optimization dimension, the 2-kHz control deadline, and the separated 50-Hz adaptation rate, so real-time requirements are stated independently of any processor-specific desktop timing.

1.5 Main Contributions and Objectives

In response to the four gaps identified above, the main contributions of this paper are as follows.

Contribution 1. A fault-constrained state-space model is derived in the fundamental (α_1 - β_1), third-harmonic (α_3 - β_3), and fifth-harmonic (α_5 - β_5) subspaces for one open phase and two adjacent open phases. The fault matrices are given explicitly through the phase-current projection operators, rather than being left as undefined symbols.

Contribution 2. A low-order adaptive estimation and reference-optimization layer is developed based on an EKF and a WRLS update. The harmonic-reference objective is written consistently as $\min J_H = \lambda_1 (T_{\text{ripple}}/T_b)^2 + \lambda_2 (P_{\text{copper}}/P_b)^2$, with $\lambda_1, \lambda_2 \geq 0$ and $\lambda_1 + \lambda_2 = 1$, subject to current and harmonic-amplitude constraints.

Contribution 3. An ENMPC is formulated with an explicitly stated prediction model, variable-horizon rule, stage cost, hard current/voltage constraints, terminal cost, and terminal invariant-set constraint. The lower layer tracks electromagnetic torque together with the optimized third- and fifth-harmonic current references.

Contribution 4. The integrated two-layer controller is evaluated on the previously designed 1-MW, four-pole seven-phase induction-motor plant [11] under healthy, one-phase-open, and adjacent two-phase-open scenarios. The 1-MW electromagnetic-thermal design is used only as the plant parameterization; the fault-state derivation, the EKF/WRLS layer, the harmonic-reference optimization, the ENMPC formulation, and the fault-control results reported here are distinct from that earlier machine-design contribution.

The contribution is therefore not claimed for any of these ingredients in isolation. Harmonic injection, predictive control, and multiphase fault tolerance all have established prior art [3, 8, 9, 7, 15, 17, 18, 21, 22]. The specific novelty examined here is their co-design as a fault-constrained hierarchical architecture for a seven-phase induction motor: the upper layer estimates slowly varying parameters and updates harmonic references, while the lower ENMPC tracks those references together with torque under explicit constraints. This positioning narrows the broader “first-time integration” framing found in earlier literature and makes the boundary with existing predictive and harmonic-injection methods explicit.

The remainder of the paper is organized as follows. Section 2 develops the seven-phase motor, transformation, open-phase fault, torque, inverter, and modulation models. Section 3 formulates the hierarchical EKF/WRLS harmonic optimizer, the ENMPC, the estimator convergence conditions, the closed-loop stability argument, and the computational design envelope. Section 4 presents the MATLAB/Simulink study, its deterministic interpretation, a comparison with recent predictive-control architectures, and the torque/torque-ripple results. Section 5 states the conclusions, limitations, and specific directions for experimental extension.

2 System Modeling

Figure 1 shows the overall power-supply and drive topology considered in this study: a multi-phase AC source feeds a rectifier and DC link, which in turn supplies the seven-phase inverter driving the induction motor.

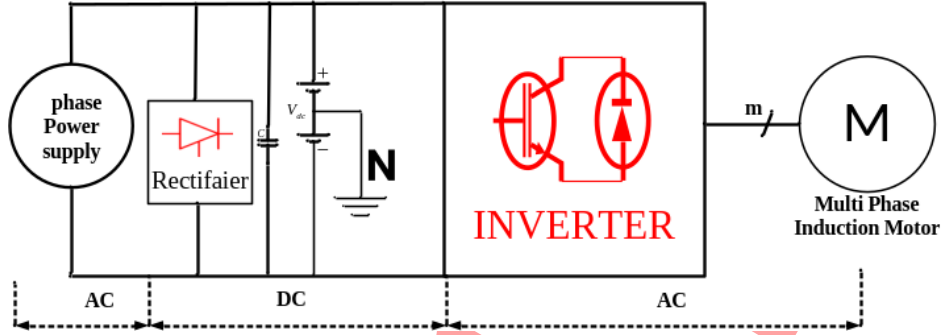


Figure 1: Power supply topology for multiphase induction motors

2.1 Dynamic Model of a Seven-Phase Induction Motor in Natural State Space

The voltage equations of the stator and rotor in the stationary reference frame are

$$\mathbf{v}_s = R_s \mathbf{i}_s + \frac{d\psi_s}{dt}, \quad (1)$$

$$\mathbf{v}_r = R_r \mathbf{i}_r + \frac{d\psi_r}{dt} - j\omega_r \psi_r, \quad (2)$$

where $\mathbf{v}_s$, $\mathbf{i}_s$, ψ_s are seven-phase vectors of stator voltage, current, and flux linkage, respectively; $\mathbf{i}_r$, ψ_r are seven-phase vectors of rotor current and flux linkage (referred to the stator); R_s and R_r are the stator and rotor resistances; and ω_r is the rotor electrical speed.

The flux-linkage equations are

$$\psi_s = L_s \mathbf{i}_s + L_m \mathbf{i}_r, \quad (3)$$

$$\psi_r = L_m \mathbf{i}_s + L_r \mathbf{i}_r, \quad (4)$$

where L_s , L_r , and L_m are the stator, rotor, and magnetizing inductances, respectively.

2.2 Generalized Clarke Transformation (GCC) for a Seven-Phase System

Using the transformation matrix $\mathbf{T}_{7s/7r}$, defined based on the Generalized Clarke Transformation for seven phases, the seven-phase variables are mapped onto seven independent variables

spanning different subspaces:

$$\mathbf{x}_{7r} = \mathbf{T}_{7s/7r} \mathbf{x}_{7s}. \quad (5)$$

The output of this transformation comprises the following subspaces:

- *Fundamental subspace* (α_1 - β_1): corresponds to the primary electromagnetic torque production.
- *Third-harmonic subspace* (α_3 - β_3): corresponds to the third-order harmonic components.
- *Fifth-harmonic subspace* (α_5 - β_5): corresponds to the fifth-order harmonic components.
- *Zero-sequence subspace* (z): relevant for systems with a separate neutral wire.

The transformation matrix $\mathbf{T}_{7s/7r}$ is defined as

$$\mathbf{T}_{7s/7r} = \frac{2}{7} \begin{bmatrix} 1 & \cos \alpha & \cos 2\alpha & \cos 3\alpha & \cos 4\alpha & \cos 5\alpha & \cos 6\alpha \\ 0 & \sin \alpha & \sin 2\alpha & \sin 3\alpha & \sin 4\alpha & \sin 5\alpha & \sin 6\alpha \\ 1 & \cos 3\alpha & \cos 6\alpha & \cos 9\alpha & \cos 12\alpha & \cos 15\alpha & \cos 18\alpha \\ 0 & \sin 3\alpha & \sin 6\alpha & \sin 9\alpha & \sin 12\alpha & \sin 15\alpha & \sin 18\alpha \\ 1 & \cos 5\alpha & \cos 10\alpha & \cos 15\alpha & \cos 20\alpha & \cos 25\alpha & \cos 30\alpha \\ 0 & \sin 5\alpha & \sin 10\alpha & \sin 15\alpha & \sin 20\alpha & \sin 25\alpha & \sin 30\alpha \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}, \quad (6)$$

where $\alpha = 2\pi/7$.

2.3 Enhanced State-Space Model Under Open-Phase Fault Conditions

After applying the GCC transformation and eliminating the equations associated with the open phases, the enhanced state-space model of the system under fault conditions is derived.

For a single-phase open fault (e.g., phase 'a'):

$$\frac{d}{dt} \begin{bmatrix} i_{s,\alpha\beta 1} \\ i_{s,\alpha\beta 3} \\ i_{s,\alpha\beta 5} \\ \psi_{r,\alpha\beta} \end{bmatrix} = \mathbf{A}_{1\text{ph-fault}} \begin{bmatrix} i_{s,\alpha\beta 1} \\ i_{s,\alpha\beta 3} \\ i_{s,\alpha\beta 5} \\ \psi_{r,\alpha\beta} \end{bmatrix} + \mathbf{B}_{1\text{ph-fault}} \begin{bmatrix} v_{s,\alpha\beta 1} \\ v_{s,\alpha\beta 3} \\ v_{s,\alpha\beta 5} \end{bmatrix}. \quad (7)$$

For a two-phase adjacent open fault (e.g., phases 'a' and 'b'):

$$\frac{d}{dt} \begin{bmatrix} i_{s,\alpha\beta 1} \\ i_{s,\alpha\beta 3} \\ i_{s,\alpha\beta 5} \\ \psi_{r,\alpha\beta} \end{bmatrix} = \mathbf{A}_{2\text{ph-fault}} \begin{bmatrix} i_{s,\alpha\beta 1} \\ i_{s,\alpha\beta 3} \\ i_{s,\alpha\beta 5} \\ \psi_{r,\alpha\beta} \end{bmatrix} + \mathbf{B}_{2\text{ph-fault}} \begin{bmatrix} v_{s,\alpha\beta 1} \\ v_{s,\alpha\beta 3} \\ v_{s,\alpha\beta 5} \end{bmatrix}. \quad (8)$$

The fault matrices are derived by directly imposing the phase-current constraints on the six non-zero-sequence GCC coordinates. This approach explicitly reveals the resulting coupling terms and eliminates the need to treat $\mathbf{A}_{1\text{ph-fault}}$ and $\mathbf{A}_{2\text{ph-fault}}$ as unspecified black-box matrices.

Let the state and input vectors be defined as

$$\mathbf{x} = [i_{\alpha 1}, i_{\beta 1}, i_{\alpha 3}, i_{\beta 3}, i_{\alpha 5}, i_{\beta 5}, \psi_{r\alpha}, \psi_{r\beta}]^T$$

and

$$\mathbf{u} = [v_{\alpha 1}, v_{\beta 1}, v_{\alpha 3}, v_{\beta 3}, v_{\alpha 5}, v_{\beta 5}]^T.$$

The following parameters are introduced:

$$\begin{aligned} L_\sigma &= L_s - \frac{L_m^2}{L_r}, \quad \tau_r = \frac{L_r}{R_r}, \quad a_1 = \frac{R_s + R_r(L_m/L_r)^2}{L_\sigma}, \\ b_1 &= \frac{R_r L_m}{L_r^2 L_\sigma}, \quad c_1 = \frac{L_m}{L_r L_\sigma}, \quad d_1 = \frac{1}{L_\sigma}, \quad e = \frac{L_m}{\tau_r}, \quad f = \frac{1}{\tau_r}. \end{aligned} \quad (9)$$

For the third- and fifth-harmonic planes, the corresponding parameters are defined as

$$a_3 = \frac{R_s}{L_{\sigma 3}}, \quad a_5 = \frac{R_s}{L_{\sigma 5}}, \quad d_3 = \frac{1}{L_{\sigma 3}}, \quad d_5 = \frac{1}{L_{\sigma 5}}.$$

These definitions provide the required compact notation for expressing the healthy and fault-coupled state-space matrices explicitly.

With $\mathbf{i} = [i_{\alpha 1}, i_{\beta 1}, i_{\alpha 3}, i_{\beta 3}, i_{\alpha 5}, i_{\beta 5}]^T$ and $\boldsymbol{\psi} = [\psi_{r\alpha}, \psi_{r\beta}]^T$, the healthy-state matrix is partitioned as

$$\mathbf{A}_h = \begin{bmatrix} \mathbf{A}_{ii} & \mathbf{A}_{i\psi} \\ \mathbf{A}_{\psi i} & \mathbf{A}_{\psi\psi} \end{bmatrix}, \quad \mathbf{A}_{ii} = \text{diag}(-a_1, -a_1, -a_3, -a_3, -a_5, -a_5), \quad (10)$$

$$\mathbf{A}_{i\psi} = \begin{bmatrix} b_1 & c_1 \omega_r \\ -c_1 \omega_r & b_1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad \mathbf{A}_{\psi i} = \begin{bmatrix} e & 0 & 0 & 0 & 0 & 0 \\ 0 & e & 0 & 0 & 0 & 0 \end{bmatrix}, \quad \mathbf{A}_{\psi\psi} = \begin{bmatrix} -f & -\omega_r \\ \omega_r & -f \end{bmatrix}, \quad (11)$$

and $\mathbf{B}_i = \text{diag}(d_1, d_1, d_3, d_3, d_5, d_5)$, so that

$$\mathbf{B}_h = \begin{bmatrix} \mathbf{B}_i \\ \mathbf{0}_{2 \times 6} \end{bmatrix}. \quad (12)$$

For an open phase 'a', the inverse-GCC condition $i_a = 0$ gives $\mathbf{c}_a^T \mathbf{i} = 0$ with $\mathbf{c}_a = [1, 0, 1, 0, 1, 0]^T$. The orthogonal projection onto the admissible current subspace is

$$\mathbf{P}_a = \begin{bmatrix} 2/3 & 0 & -1/3 & 0 & -1/3 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ -1/3 & 0 & 2/3 & 0 & -1/3 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ -1/3 & 0 & -1/3 & 0 & 2/3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \quad (13)$$

The single-open-phase matrices are therefore explicitly

$$\mathbf{A}_{1\text{ph}} = \begin{bmatrix} \mathbf{P}_a \mathbf{A}_{ii} \mathbf{P}_a & \mathbf{P}_a \mathbf{A}_{i\psi} \\ \mathbf{A}_{\psi i} \mathbf{P}_a & \mathbf{A}_{\psi\psi} \end{bmatrix}, \quad \mathbf{B}_{1\text{ph}} = \begin{bmatrix} \mathbf{P}_a \mathbf{B}_i \\ \mathbf{0}_{2 \times 6} \end{bmatrix}. \quad (14)$$

The off-diagonal entries created by $\mathbf{P}_a$ are the analytical coupling terms between the fundamental, third-, and fifth-harmonic planes.

For reproducibility, the cross-subspace coupling can be displayed explicitly without expanding the complete 8×8 matrix. Restricting $\mathbf{P}_a \mathbf{A}_{ii} \mathbf{P}_a$ to the α -coordinate subset $(\alpha_1, \alpha_3, \alpha_5)$ gives

$$(\mathbf{P}_a \mathbf{A}_{ii} \mathbf{P}_a)|_{\alpha} = \frac{1}{9} \begin{bmatrix} -(4a_1 + a_3 + a_5) & 2a_1 + 2a_3 - a_5 & 2a_1 - a_3 + 2a_5 \\ 2a_1 + 2a_3 - a_5 & -(a_1 + 4a_3 + a_5) & -a_1 + 2a_3 + 2a_5 \\ 2a_1 - a_3 + 2a_5 & -a_1 + 2a_3 + 2a_5 & -(a_1 + a_3 + 4a_5) \end{bmatrix}. \quad (15)$$

Thus, for instance, the $\alpha_1 \leftrightarrow \alpha_3$ coupling coefficient is $(2a_1 + 2a_3 - a_5)/9$, whereas the $\alpha_1 \leftrightarrow \alpha_5$ coupling coefficient is $(2a_1 - a_3 + 2a_5)/9$. These non-zero off-diagonal terms arise solely from the open-phase projection, while the β coordinates remain uncoupled by $\mathbf{P}_a$ in the phase- a fault case. This explicit derivation makes the cross-subspace coupling structure of $\mathbf{A}_{1\text{ph}}$ analytically transparent.

For the case of adjacent open phases a and b , let $\alpha = 2\pi/7$ and define

$$\mathbf{c}_b = [\cos \alpha, \sin \alpha, \cos 3\alpha, \sin 3\alpha, \cos 5\alpha, \sin 5\alpha]^{\top},$$

$$\mathbf{C}_{ab} = [\mathbf{c}_a^{\top}; \mathbf{c}_b^{\top}], \quad \mathbf{P}_{ab} = \mathbf{I}_6 - \mathbf{C}_{ab}^{\top} (\mathbf{C}_{ab} \mathbf{C}_{ab}^{\top})^{-1} \mathbf{C}_{ab}.$$

Here, $\mathbf{P}_{ab}$ projects the six non-zero-sequence GCC coordinates onto the admissible subspace associated with the simultaneous open-phase constraints. Numerically,

$$\mathbf{P}_{ab} = \begin{bmatrix} 0.452605 & -0.211807 & -0.134403 & -0.117544 & -0.318202 & 0.264118 \\ -0.211807 & 0.790425 & 0.196834 & -0.116305 & 0.014972 & 0.261336 \\ -0.134403 & 0.196834 & 0.481798 & 0.109235 & -0.347395 & -0.245449 \\ -0.117544 & -0.116305 & 0.109235 & 0.935455 & 0.008309 & 0.145030 \\ -0.318202 & 0.014972 & -0.347395 & 0.008309 & 0.665597 & -0.018670 \\ 0.264118 & 0.261336 & -0.245449 & 0.145030 & -0.018670 & 0.674120 \end{bmatrix}. \quad (16)$$

Accordingly,

$$\mathbf{A}_{2\text{ph}} = \begin{bmatrix} \mathbf{P}_{ab}\mathbf{A}_{ii}\mathbf{P}_{ab} & \mathbf{P}_{ab}\mathbf{A}_{i\psi} \\ \mathbf{A}_{\psi i}\mathbf{P}_{ab} & \mathbf{A}_{\psi\psi} \end{bmatrix}, \quad \mathbf{B}_{2\text{ph}} = \begin{bmatrix} \mathbf{P}_{ab}\mathbf{B}_i \\ \mathbf{0}_{2 \times 6} \end{bmatrix}. \quad (17)$$

Because $\mathbf{P}_{ab}$ is non-diagonal, the two-phase fault creates stronger cross-subspace coupling than the one-phase constraint. These expressions are the matrices used directly by the predictive model; no additional empirical coupling coefficients are introduced.

2.4 Electromagnetic Torque Model

The electromagnetic torque is calculated from the current and flux components as

$$T_e = \frac{P}{2} \cdot \frac{L_m}{L_r} (\psi_{r,\alpha} i_{s,\beta 1} - \psi_{r,\beta} i_{s,\alpha 1}) + T_{e,\text{ripple}}, \quad (18)$$

where P is the number of poles. The torque-ripple component $T_{e,\text{ripple}}$ is directly related to the harmonic current components in the α_3 - β_3 and α_5 - β_5 subspaces, as well as their coupling with the rotor fluxes, and can be modeled as

$$T_{e,\text{ripple}} = f(i_{s,\alpha 3}, i_{s,\beta 3}, i_{s,\alpha 5}, i_{s,\beta 5}, \psi_{r,\alpha}, \psi_{r,\beta}). \quad (19)$$

2.5 Seven-Phase Inverter Model

The drive is supplied by a two-level, seven-leg voltage-source inverter connected to a common dc link. In the present control architecture, the inverter is modeled as the actuator that maps the six non-zero-sequence ENMPC voltage commands to the seven stator phase voltages; general three-phase converter background is therefore omitted.

Seven-phase SVPWM provides the interface between the continuous voltage reference and the admissible switching states. The modulation model below is retained only to define this control interface, the switching-state set, and the mapping of voltage harmonics into the fundamental, third-harmonic, fifth-harmonic, and zero-sequence subspaces.

2.6 Space Vector Modulation (SVM) in Seven-Phase Drives

For a two-level n -phase inverter, each converter leg has two admissible switching states; therefore the switching set contains 2^n combinations. For $n = 7$, the converter has $2^7 = 128$ switching states. This elementary count is consistent with seven-phase SVPWM formulations,

which map the 128 switching combinations onto the orthogonal vector-space subspaces [2]. The switching functions are denoted $\mathbf{s} = [s_a, s_b, s_c, s_d, s_e, s_f, s_g]^\top$, with $s_j \in \{0, 1\}$.

The modulation-stage subspace mapping uses the same GCC operator introduced in Section 2.2; the full 7×7 matrix is therefore not repeated. In compact form, the seven-phase voltage vector $\mathbf{v}_s$ is mapped as

$$\mathbf{v}_{\text{GCC}} = \mathbf{T}_7 \mathbf{v}_s, \quad (20)$$

where $\mathbf{T}_7$ is the transformation matrix defined in (6). This transformation maps harmonic components into three subspaces as follows:

- (a) the fundamental harmonic and components of order $k = 1 \pm 14m$ are mapped to the α_1 - β_1 plane;
- (b) the harmonic components of order $k = 3 \pm 14m$ and $k = 5 \pm 14m$ are mapped to the α_3 - β_3 and α_5 - β_5 planes, respectively;
- (c) the harmonic components of order $k = 7 \pm 14m$ are mapped to the zero-sequence plane (x_0).

The values of k and m are defined as $k = 1, 2, 3, \dots$ and $m = 0, 1, 2, 3, \dots$

2.7 Inverter Circuit and Specifications

The circuit and structure of the two-level seven-phase inverter are shown in Figure 2. The corresponding output-voltage waveforms are shown in Figure 3. The topology contains fourteen controllable devices, two per phase leg, and supplies the seven stator phases a – g from the common dc link.

Semiconductor selection for a megawatt-class inverter is governed by dc-link voltage, phase current, switching loss, thermal limits, and the required modulation rate. The control study therefore specifies the commanded voltage and update rate independently of any particular IGBT module or gate-driver implementation.

3 Proposed Hierarchical Harmonic Optimization and ENMPC

Notation convention. Lower-case bold symbols denote vectors, upper-case symbols denote matrices or admissible sets, $(\cdot)^\top$ denotes transpose, $(\cdot)^{-1}$ denotes matrix inverse, $(\cdot)^*$ denotes a reference/optimal quantity, $\hat{(\cdot)}$ denotes a state or parameter estimate, and a tilde denotes a normalized per-unit quantity. The fault index $F \in \{h, 1\text{ph}, 2\text{ph}\}$ identifies the active healthy,

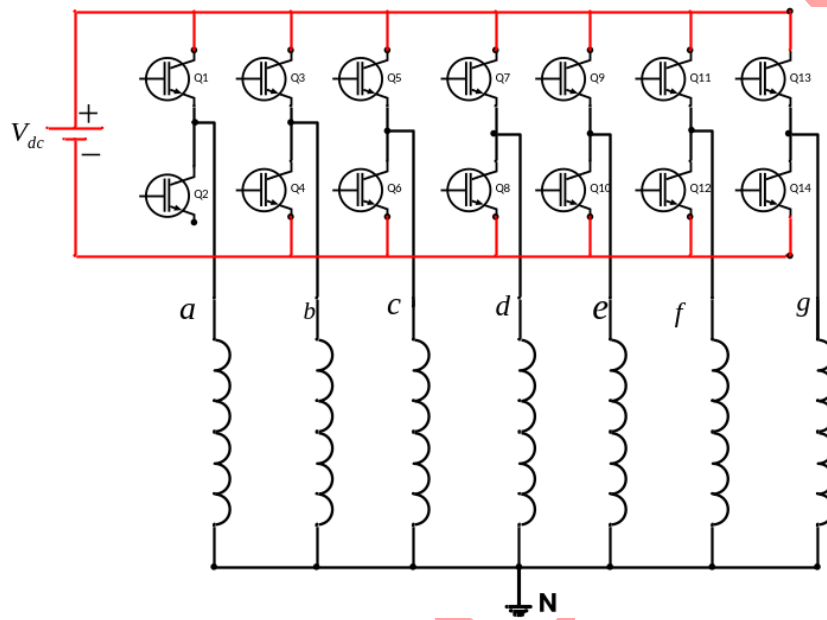


Figure 2: Circuit diagram of the seven-phase inverter connected to a seven-phase motor

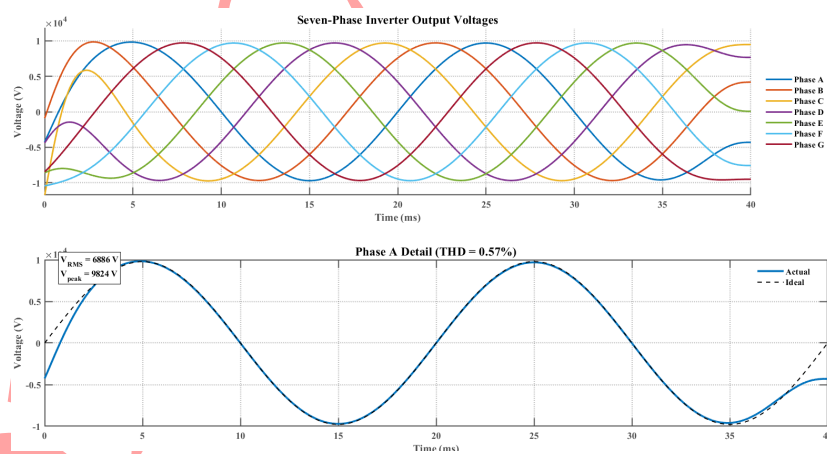


Figure 3: Inverter output voltage waveforms

one-open-phase, or adjacent-two-open-phase model. The harmonic-current vector $\mathbf{i}_h$ collects the α_3 - β_3 and α_5 - β_5 components. All symbols used by the controller are defined before their first optimization or estimation equation.

Physical motivation for the hierarchical controller. An open stator phase imposes a current constraint that destroys the orthogonality of the GCC subspaces in the physical phase variables; fundamental current commands can therefore excite the α_3 - β_3 and α_5 - β_5 planes and increase torque pulsation. With two adjacent open phases, the admissible current subspace is further reduced, and RMS current is redistributed among the remaining phases. This mechanism motivates the architecture below: the upper layer updates admissible harmonic-current references, while the ENMPC allocates voltage under the fault-constrained model and explicit current/voltage limits.

3.1 Hierarchical Architecture and Harmonic-Reference Objective

The controller is organized in two rates. The upper layer estimates the states and slowly varying electrical parameters and then updates the third- and fifth-harmonic references. The lower layer solves the ENMPC problem at every control sample. The two-rate structure avoids embedding parameter identification and harmonic-reference search inside every predictive-control iteration.

Let $\boldsymbol{\rho} = [A_3, \varphi_3, A_5, \varphi_5]^\top$ denote the harmonic-reference parameters. The upper layer is formulated in normalized coordinates so that torque-ripple suppression and copper-loss reduction are compared on the same scale. Define

$$\varepsilon_T(\boldsymbol{\rho}) = \left[\frac{T_{\text{ripple}}(\boldsymbol{\rho})}{T_b} \right]^2, \quad \varepsilon_P(\boldsymbol{\rho}) = \left[\frac{P_{\text{copper}}(\boldsymbol{\rho})}{P_b} \right]^2, \quad (21)$$

where T_b and P_b are the rated torque and power bases, respectively.

The weighting is updated from the two normalized objective components rather than imposed as an undocumented fixed pair:

$$\lambda_1(k) = \frac{\varepsilon_T(k)}{\varepsilon_T(k) + \varepsilon_P(k)}, \quad \lambda_2(k) = \frac{\varepsilon_P(k)}{\varepsilon_T(k) + \varepsilon_P(k)}, \quad (22)$$

with $\lambda_1 = \lambda_2 = 0.5$ holding only at the zero-error point. The harmonic-reference problem is therefore

$$\min_{\boldsymbol{\rho}} J_H(\boldsymbol{\rho}) = \lambda_1(k) \varepsilon_T(\boldsymbol{\rho}) + \lambda_2(k) \varepsilon_P(\boldsymbol{\rho}), \quad (23)$$

subject to the phase-current limit and admissible third- and fifth-harmonic amplitude bounds.

This self-scaling formulation removes dependence on the physical units of torque and loss and gives larger instantaneous emphasis to the normalized objective that is farther from its

desired value. The optimizer updates ρ after a valid estimator update; if the candidate violates the current or voltage constraints, the previous feasible harmonic reference is retained.

The four-parameter problem (23) is implemented as a bounded nonlinear program and solved at the 50-Hz upper-layer rate by a warm-started sequential quadratic programming (SQP) routine, initialized from the previous feasible ρ . The previous solution is also the fallback reference. The SQP iterations are deadline-limited to the 20-ms upper-layer period; at the deadline, the best feasible iterate is accepted, and if no improved feasible point is available, the previous feasible ρ is retained. This rule prevents the harmonic-reference update from overrunning the upper-layer schedule while preserving feasibility.

3.2 Two-Level EKF/WRLS Estimator

The first estimation level employs an extended Kalman filter (EKF) to estimate the electrical state variables. For the active fault configuration $F \in \{h, 1ph, 2ph\}$, the discrete-time prediction and correction steps are given by

$$\begin{aligned}\hat{\mathbf{x}}(k|k-1) &= \mathbf{f}_F(\hat{\mathbf{x}}(k-1|k-1), \mathbf{u}(k-1), \hat{\boldsymbol{\theta}}(k-1)), \\ \mathbf{P}(k|k-1) &= \mathbf{F}(k)\mathbf{P}(k-1|k-1)\mathbf{F}^\top(k) + \mathbf{Q}(k),\end{aligned}\quad (24)$$

$$\begin{aligned}\mathbf{K}(k) &= \mathbf{P}(k|k-1)\mathbf{H}^\top(k) [\mathbf{H}(k)\mathbf{P}(k|k-1)\mathbf{H}^\top(k) + \mathbf{R}(k)]^{-1}, \\ \hat{\mathbf{x}}(k|k) &= \hat{\mathbf{x}}(k|k-1) + \mathbf{K}(k) [\mathbf{y}(k) - \mathbf{h}(\hat{\mathbf{x}}(k|k-1))],\end{aligned}\quad (25)$$

$$\mathbf{P}(k|k) = [\mathbf{I} - \mathbf{K}(k)\mathbf{H}(k)] \mathbf{P}(k|k-1). \quad (26)$$

Here, $\mathbf{F}(k) = \partial \mathbf{f}_F / \partial \mathbf{x}$ and $\mathbf{H}(k) = \partial \mathbf{h} / \partial \mathbf{x}$ denote the Jacobian matrices of the state-transition and measurement functions, respectively, evaluated at the predicted state. The measurement vector is defined as

$$\mathbf{y}(k) = [i_{\alpha 1}, i_{\beta 1}, i_{\alpha 3}, i_{\beta 3}, i_{\alpha 5}, i_{\beta 5}, \omega_r]^\top. \quad (27)$$

All estimated states and slowly varying parameters are represented in per-unit (p.u.) coordinates based on the rated machine quantities. The initial error covariance matrix is set to

$$\mathbf{P}(0|0) = \mathbf{I}. \quad (28)$$

Rather than employing fixed process- and measurement-noise covariance matrices, $\mathbf{Q}(k)$ and $\mathbf{R}(k)$ are updated online using covariance matching based on the accumulated state-correction and innovation sequences. Specifically, define

$$\boldsymbol{\delta}_k = \hat{\mathbf{x}}(k|k) - \hat{\mathbf{x}}(k|k-1), \quad \boldsymbol{\nu}_k = \mathbf{y}(k) - \mathbf{h}(\hat{\mathbf{x}}(k|k-1)). \quad (29)$$

The corresponding adaptive covariance estimates are then obtained as

$$\mathbf{Q}(k) = \text{diag} \left\{ \frac{1}{k} \sum_{j=1}^k (\delta_j \odot \delta_j) \right\}, \quad (30)$$

$$\mathbf{R}(k) = \text{diag} \left\{ \frac{1}{k} \sum_{j=1}^k (\nu_j \odot \nu_j) \right\}, \quad (31)$$

where $\odot$ denotes the Hadamard (element-wise) product. A small positive numerical floor is imposed on the diagonal elements of $\mathbf{Q}(k)$ and $\mathbf{R}(k)$ only when necessary to preserve their nonsingularity.

The second estimation level employs a covariance-weighted recursive least-squares (WRLS) scheme to update the slowly varying parameter vector

$$\boldsymbol{\theta} = [R_s, R_r, L_\sigma, L_{\sigma 3}, L_{\sigma 5}, L_m, L_r]^\top. \quad (32)$$

To account for the time-varying reliability of the measurements, the regression equation is prewhitened using the current measurement-noise covariance matrix. Accordingly, the weighted measurement vector and regressor are defined as

$$\mathbf{z}_w(k) = \mathbf{R}^{-1/2}(k) \mathbf{z}(k), \quad \boldsymbol{\varphi}_w(k) = \mathbf{R}^{-1/2}(k) \boldsymbol{\varphi}(k). \quad (33)$$

No exponential forgetting is employed, i.e., $\gamma = 1$. Thus, the adaptation is determined exclusively by the data-dependent covariance weighting and does not involve an additional empirically selected forgetting factor. The WRLS update equations are given by

$$\begin{aligned} \mathbf{K}_\theta(k) &= \frac{\mathbf{P}_\theta(k-1) \boldsymbol{\varphi}_w(k)}{1 + \boldsymbol{\varphi}_w^\top(k) \mathbf{P}_\theta(k-1) \boldsymbol{\varphi}_w(k)}, \\ \hat{\boldsymbol{\theta}}(k) &= \hat{\boldsymbol{\theta}}(k-1) + \mathbf{K}_\theta(k) [\mathbf{z}_w(k) - \boldsymbol{\varphi}_w^\top(k) \hat{\boldsymbol{\theta}}(k-1)], \end{aligned} \quad (34)$$

$$\mathbf{P}_\theta(k) = [\mathbf{I} - \mathbf{K}_\theta(k) \boldsymbol{\varphi}_w^\top(k)] \mathbf{P}_\theta(k-1). \quad (35)$$

The parameter vector is initialized at unity in per-unit coordinates, corresponding to the rated operating point of the published 1-MW plant model [11], and is subsequently updated online. Therefore, the ENMPC employs the current estimate $\hat{\boldsymbol{\theta}}(k)$ rather than assuming invariant resistive and inductive parameters under variations in temperature, loading conditions, or post-fault operating conditions. The feasibility of EKF-based online parameter adaptation for multiphase induction motor drives has also been experimentally demonstrated in related studies [16].

3.2.1 Estimator Admissibility and Convergence Conditions

The recursive estimator is constrained to the physically admissible parameter set $\Theta = \{\boldsymbol{\theta} : \boldsymbol{\theta}_{\min} \leq \boldsymbol{\theta} \leq \boldsymbol{\theta}_{\max}, R_s > 0, R_r > 0, L_\sigma > 0, L_{\sigma 3} > 0, L_{\sigma 5} > 0, L_m > 0, L_r > 0\}$.

After each WRLS update, $\hat{\theta}(k)$ is projected onto Θ . The covariance floors used in $\mathbf{Q}(k)$ and $\mathbf{R}(k)$ preserve positive definiteness of the innovation covariance, while $\mathbf{P}_\theta(0) \succ 0$ preserves the WRLS covariance recursion.

For the regression sequence, the standard persistence-of-excitation condition is

$$\sum_{j=k}^{k+N_e-1} \varphi_w(j) \varphi_w(j)^\top \succeq \alpha_e \mathbf{I}, \quad (36)$$

for some finite N_e and $\alpha_e > 0$. Under bounded regressors and bounded measurement noise, this condition keeps the WRLS parameter error bounded; in the noise-free case it yields convergence of the identifiable parameter components. The EKF statement is correspondingly local: bounded Jacobians, positive-definite $\mathbf{Q}$ and $\mathbf{R}$, and local observability of $(\mathbf{F}(k), \mathbf{H}(k))$ provide a bounded state-estimation error in the neighborhood in which the linearization is valid. These are the convergence conditions used by the two-level estimator and are distinct from the closed-loop Lyapunov conditions of Section 3.4.

3.3 Enhanced Nonlinear Model Predictive Controller

At sampling instant k , the active fault model is discretized according to

$$\mathbf{x}(k+1) = \mathbf{f}_F[\mathbf{x}(k), \mathbf{u}(k), \hat{\theta}(k)]. \quad (37)$$

Let

$$\mathbf{i}_h = [i_{\alpha 3}, i_{\beta 3}, i_{\alpha 5}, i_{\beta 5}]^\top, \quad e_T = T_e - T_e^*, \quad (38)$$

denote the harmonic-current vector and electromagnetic torque tracking error, respectively. The corresponding normalized quantities are defined as

$$\tilde{e}_T = \frac{e_T}{T_b}, \quad \tilde{\mathbf{e}}_h = \mathbf{D}_i^{-1} (\mathbf{i}_h - \mathbf{i}_h^*), \quad \Delta \tilde{\mathbf{u}} = \mathbf{D}_v^{-1} \Delta \mathbf{u}, \quad (39)$$

where T_b is the torque base, while $\mathbf{D}_i$ and $\mathbf{D}_v$ contain the admissible harmonic-current and phase-voltage scales, respectively.

The normalization matrices are constructed directly from the admissible bounds imposed by the controller:

$$\begin{aligned} \mathbf{D}_i &= \text{diag}(I_{\alpha 3, \max}, I_{\beta 3, \max}, I_{\alpha 5, \max}, I_{\beta 5, \max}), \\ \mathbf{D}_v &= \text{diag}(V_{\alpha 1, \max}, V_{\beta 1, \max}, V_{\alpha 3, \max}, V_{\beta 3, \max}, V_{\alpha 5, \max}, V_{\beta 5, \max}). \end{aligned} \quad (40)$$

For symmetric current and voltage bounds, these matrices simplify to

$$\mathbf{D}_i = I_{h, \max} \mathbf{I}_4, \quad \mathbf{D}_v = V_{\max} \mathbf{I}_6. \quad (41)$$

Accordingly, the normalized stage-cost terms are scaled using the same admissible current and voltage limits that define the controller constraint set in (43). This normalization therefore does not introduce additional empirical scaling factors or tuning weights.

The ENMPC objective function is formulated using normalized variables to eliminate dimensional inconsistencies and ambiguity in the relative weighting of the different performance terms:

$$\min_U J_N = \sum_{j=0}^{N_p(k)-1} \left\{ \tilde{e}_T^2(k+j|k) + \|\tilde{\mathbf{e}}_h(k+j|k)\|_2^2 + \|\Delta\tilde{\mathbf{u}}(k+j|k)\|_2^2 \right\} + \mathbf{e}_x^\top(k+N_p|k)\mathbf{P}_f\mathbf{e}_x(k+N_p|k). \quad (42)$$

Hence, the stage-cost terms have unit weights after normalization, while the terminal weighting matrix $\mathbf{P}_f$ is computed from the discrete-time Riccati equation associated with the local terminal linearization, rather than being introduced as an independently tuned empirical matrix. The optimization problem is subject to the following state, input, current, voltage, and terminal-set constraints:

$$\begin{aligned} \mathbf{x}(k+j|k) &\in X, & \mathbf{u}(k+j|k) &\in U, & \|i_{\text{phase}}(k+j|k)\| &\leq I_{\max}, \\ \|v_{\text{phase}}(k+j|k)\| &\leq V_{\max}, & \mathbf{e}_x(k+N_p|k) &\in X_f. \end{aligned} \quad (43)$$

The prediction horizon is adjusted online according to the normalized tracking indicator

$$\eta(k) = \frac{\|\mathbf{e}_x(k)\|}{e_b} + \frac{|e_T(k)|}{T_b}. \quad (44)$$

For a fundamental electrical frequency of 50 Hz, the electrical period is $T_e = 20$ ms. The electrical-state EKF correction and the ENMPC optimization are performed at the lower-layer sampling period $T_s = T_e/40 = 0.5$ ms (2 kHz), whereas the WRLS parameter update and harmonic-reference optimization are performed once per electrical cycle (50 Hz). The adaptive prediction-horizon law is defined as

$$N_p(k) = 2 + \left\lceil \frac{8\eta(k)}{1 + \eta(k)} \right\rceil, \quad (45)$$

which yields $2 \leq N_p \leq 10$. Accordingly, the prediction window ranges from 1 to 5 ms, increasing during fault transients when the tracking error is large and decreasing as the system approaches steady-state operation.

At each sampling instant, the ENMPC decision vector is defined by

$$U_k = \text{col} \{ \mathbf{u}(k|k), \dots, \mathbf{u}(k+N_p-1|k) \} \in \mathbb{R}^{6N_p}. \quad (46)$$

Therefore, the online optimization problem involves between 12 and 60 voltage decision variables, depending on the adaptive prediction horizon. Feasibility is determined jointly by the

constraints in (43), the terminal invariant set X_f , and the active fault-dependent model $\mathbf{f}_F$. This explicit characterization of the decision space completes the formulation of the lower-layer EN-MPC optimization problem.

3.4 Closed-Loop Stability

The stability argument follows standard terminal-set NMPC theory [4, 14] and does not rely on distributed-computing self-stabilization. Let $\ell(\mathbf{e}, \mathbf{u})$ be the positive-definite stage cost of Section 3.3 and $V_f(\mathbf{e}) = \mathbf{e}^\top \mathbf{P}_f \mathbf{e}$ the terminal cost. Assume that X_f is positively invariant under a local admissible controller $\kappa_f(\mathbf{e})$, that the equilibrium/reference is feasible, and that the terminal decrease condition

$$V_f[\mathbf{f}_F(\mathbf{e}, \kappa_f(\mathbf{e}))] - V_f(\mathbf{e}) \leq -\ell[\mathbf{e}, \kappa_f(\mathbf{e})], \quad \mathbf{e} \in X_f, \quad (47)$$

holds. Let $V_N(\mathbf{e}_k) = J_N^*(\mathbf{e}_k)$ denote the optimal finite-horizon value. Shifting the optimal sequence by one sample and appending κ_f gives a feasible candidate at $k+1$; therefore,

$$V_N(\mathbf{e}_{k+1}) - V_N(\mathbf{e}_k) \leq -\ell(\mathbf{e}_k, \mathbf{u}_k^*) \leq -\alpha \|\mathbf{e}_k\|^2, \quad \alpha > 0. \quad (48)$$

Hence, for the nominal fault model, initial feasibility implies recursive feasibility and asymptotic convergence of the tracking error within the feasible region. If the EKF/model mismatch is bounded by $\mathbf{d}_k$ and $\mathbf{f}_F$ is locally Lipschitz, the same argument gives

$$\Delta V_N \leq -\alpha \|\mathbf{e}_k\|^2 + c \|\mathbf{d}_k\|^2. \quad (49)$$

The closed loop is therefore practically bounded with respect to bounded estimation/model errors. This is a local, constraint-dependent stability statement, not a global robust-stability claim.

3.5 Computational Burden and Real-Time Design Envelope

The computational dimensions are fixed by $n_x = 8$ states, $n_u = 6$ voltage inputs, $n_y = 7$ measurements, $n_\theta = 7$ adaptive electrical parameters, and $2 \leq N_p \leq 10$. The ENMPC therefore optimizes $n_z = 6N_p = 12\text{--}60$ voltage variables. Model propagation scales linearly with N_p , while a dense Newton/SQP factorization of the condensed constrained subproblem has the conservative worst-case scaling $O(n_z^3)$. This bound is intentionally conservative; sparse multiple-shooting or Riccati-based implementations exploit the banded prediction structure and reduce the practical factorization burden.

At the estimator level, the EKF requires one 7×7 innovation-covariance inversion at each 0.5-ms sample, together with fixed-size 8-state covariance updates. The $n_\theta = 7$ WRLS covariance update and the four-parameter harmonic-reference optimization are executed at 50 Hz rather than at every ENMPC step. Thus, the two-rate architecture separates the computationally slower parameter/reference adaptation from the 2-kHz torque/current-control loop.

For the upper layer, Equation (23) has only four decision variables. The warm-started SQP update therefore involves fixed-size four-variable subproblems (dense local factorization $O(4^3)$) and is executed only once per 20-ms electrical period. Its deadline rule is the one stated in Section 3.1: the best feasible iterate is returned at the upper-layer boundary, otherwise the previous feasible ρ is retained. Hence, the reference optimizer is explicitly included in the 20-ms upper-layer real-time envelope, rather than omitted from the computational accounting.

The implementation requirement is therefore explicit: the target control processor must complete the warm-started 12–60-variable constrained ENMPC solve, the 8-state prediction, and the EKF correction within the 0.5-ms control interval. A floating-point DSP/SoC or FPGA-assisted platform with deterministic linear-algebra support is the relevant implementation class. Processor-dependent wall-clock time is not used here as a hardware-independent performance metric; the mathematically reproducible quantities are the problem dimension, update rates, and 0.5-ms execution deadline stated above.

3.6 Performance Indices

The performance indices are evaluated from the same simulated waveform windows used in Section 4. Effective torque is the 200-ms moving average, which corresponds to ten 50-Hz electrical cycles. The remaining indices are the torque-ripple factor,

$$\text{TRF} = 100 \frac{T_{\max} - T_{\min}}{T_{\text{avg}}}, \quad (50)$$

the total harmonic distortion,

$$\text{THD} = 100 \frac{\left[\sum_{h=2}^H I_h^2 \right]^{1/2}}{I_1}, \quad (51)$$

and the stator copper loss,

$$P_{\text{copper}} = R_s \sum_{j=a}^g I_{j,\text{rms}}^2. \quad (52)$$

4 Simulation and Results

4.1 Simulation Setup

The study was implemented in MATLAB/Simulink using the seven-phase, 1-MW, four-pole induction-motor plant reported in [11]. The stator electrical frequency is 50 Hz. The simulation is divided into three intervals: healthy operation for $0 \leq t < 4$ s, a single open phase for $4 \leq t < 8$ s, and two adjacent open phases for $8 \leq t \leq 12$ s. Four control cases are compared: the conventional controller without compensation, the conventional controller with compensation, the proposed hierarchical controller without harmonic compensation, and the proposed hierarchical controller with harmonic compensation. In Figure 4 only, the legacy legend abbreviation “SS” denotes the same proposed (ENMPC) controller used in Tables 3 and 4, it is retained solely as a figure label and is not used as a control-theoretic stability concept.

For reproducibility, the plant and controller are specified on a common rated base. The repeated machine-level quantities are $P_b = 1$ MW, four poles, $f_b = 50$ Hz, and $T_b = 6.41$ kN·m; Figure 3 reports a phase-A inverter output of $V_{\text{RMS}} = 6.886$ kV and $V_{\text{peak}} = 9.824$ kV. The dimensional electromagnetic-thermal plant is the published design in [11]. In the reduced control model, R_s , R_r , L_s , L_r , and L_m are not separate hand-tuned controller constants: their rated-point values define the per-unit base, $\tilde{\theta}(0) = 1$, and the effective coefficients used by the predictor are updated online through the EKF/WRLS mechanism of Section 3.2. The lower control period, upper-layer update period, adaptive horizon law, normalized objective weighting, and covariance update rules are given explicitly in sections 3.1, 3.2, and 3.3.

The numerical comparison is deterministic and is evaluated over the three prescribed operating intervals. Effective torque is computed with a 200-ms moving-average window, equivalent to ten electrical cycles at 50 Hz. Torque-ripple factors, effective torque, and the remaining reported indices are therefore interpreted as direct simulation metrics for the stated scenarios; inferential-significance terminology is not used.

Because the state equations, initial condition, fault instants, controller update laws, and plant parameterization are deterministic, repeated runs with the same numerical configuration reproduce the same trajectory by construction. Repeating the identical simulation would therefore not create an independent sample and would yield a degenerate confidence interval. For this reason, the paper reports exact scenario metrics rather than inferential p -values. Statistical confidence intervals become meaningful only after a stochastic uncertainty model (e.g., randomized parameter distributions, sensor-noise ensembles, or Monte Carlo fault timing) is introduced; such an analysis answers a different robustness question and is not conflated with the deterministic closed-loop comparison reported here.

Table 2: Simulation, estimator, and predictive-control settings used in the numerical study

Quantity	Value / definition	Role in the model
Rated power, P_b	1 MW	Plant/base quantity
Number of stator phases	7	Seven-phase induction-motor plant
Pole number	4	Published 1-MW plant [11]
Electrical frequency, f_b	50 Hz ($T_e = 20$ ms)	Rated electrical base
Rated torque base, T_b	6.41 kN·m	Torque normalization and result reference
Phase-A inverter voltage	$V_{\text{RMS}} = 6.886$ kV; $V_{\text{peak}} = 9.824$ kV	Waveform value reported in Figure 3
Fault schedule	$t = 4$ s: first phase open; $t = 8$ s: adjacent second phase open	Healthy / one-phase / adjacent-two-phase scenarios
State dimension, n_x	8	Six stator-current components + two rotor-flux components
Control dimension, n_u	6	Voltage components in $\alpha_1\beta_1$, $\alpha_3\beta_3$, $\alpha_5\beta_5$
Measurement dimension, n_y	7	Six current components + rotor speed
Adaptive parameter dimension, n_θ	7	$R_s, R_r, L_\sigma, L_{\sigma 3}, L_{\sigma 5}, L_m, L_r$
Electrical-state EKF / ENMPC sampling	$T_s = 0.5$ ms (2 kHz)	Fast lower-layer update
WRLS and harmonic-reference update	20 ms (50 Hz)	Slow adaptive upper-layer update
Prediction horizon, N_p	2–10 samples	Adaptive ENMPC horizon
Prediction window	1–5 ms	$N_p T_s$
Initial EKF covariance	$\mathbf{P}(0 0) = \mathbf{I}$	Normalized state-estimation initialization
WRLS forgetting factor	$\gamma = 1$	Covariance-weighted recursion without exponential forgetting
$\mathbf{Q}(k), \mathbf{R}(k)$	Online covariance matching with positive numerical floor	Adaptive process/measurement covariance
Plant R_s, R_r, L_s, L_r, L_m , and mechanical J	Rated-point dimensional values of the 1-MW plant model [11]; electrical predictor coefficients updated online in per-unit form	Physical plant constants separated from controller tuning
Effective-torque averaging window	200 ms	Ten electrical cycles at 50 Hz
SVPWM command-update rate	2 kHz	Voltage reference refreshed with the lower-layer control command; semiconductor device selection is outside the reduced control model

4.2 Healthy-State Behavior

Under healthy operation, all four strategies regulate the effective torque close to the rated level. Table 3 reports 6.41 kN·m for each strategy, while Figure 4 shows the corresponding

instantaneous-torque bands. The principal difference in this interval is torque quality: Table 4 gives ripple factors of 3.1% and 2.9% for the conventional controller without and with compensation, compared with 2.5% and 2.3% for the proposed controller. Because these values come from a single deterministic simulation configuration, they are treated as numerical comparisons rather than as inferential evidence.

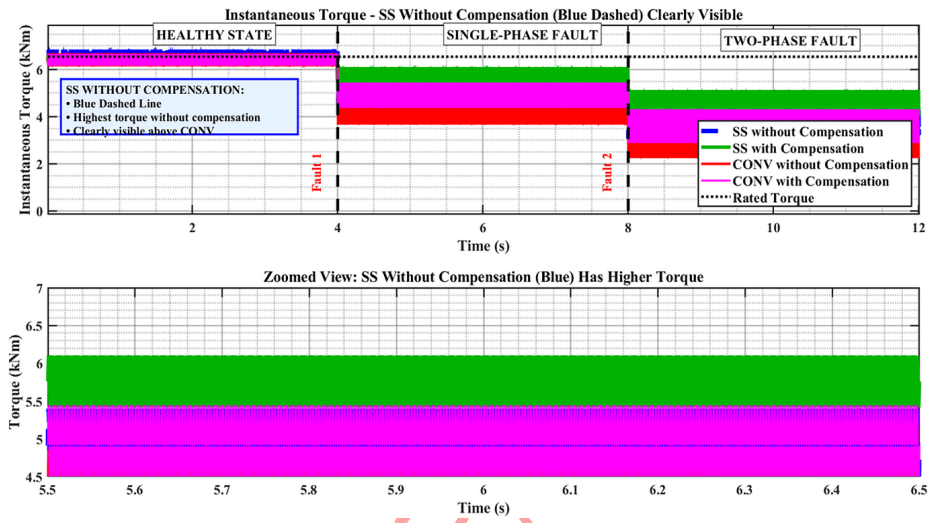


Figure 4: Instantaneous torque variations under different conditions and states

4.3 Response to a Single-Phase Open Fault

The first open-phase fault is applied at $t = 4$ s. The four trajectories separate immediately after the topology change, as shown in Figure 4.

Without harmonic compensation, the proposed controller maintains 4.91 kN·m in the single-phase-open interval, whereas the conventional uncompensated controller maintains 4.25 kN·m (Table 3). The corresponding torque-ripple factors are 7.1% and 9.9% (Table 4). Thus, the proposed state/predictive structure preserves a higher effective-torque level and a lower simulated ripple under the same fault scenario.

With compensation active, the proposed controller reaches 5.76 kN·m and a 4.8% ripple factor; the compensated conventional case reaches 4.91 kN·m and 7.8%, respectively. The improvement is attributed to simultaneous tracking of the fundamental and optimized harmonic references, rather than to an assumed instantaneous fault-detection mechanism; in the simulations, the controller is informed of the topology change at the prescribed fault time.

4.4 Response to Two Adjacent Open Phases

The second adjacent phase is opened at $t = 8$ s, leaving five healthy stator phases and producing the strongest subspace coupling considered in this study.

For two adjacent open phases, the proposed controller without harmonic compensation maintains 3.70 kN·m, compared with 2.94 kN·m for the uncompensated conventional controller. With harmonic compensation, the corresponding effective torques are 4.68 kN·m and 3.60 kN·m (Table 3).

Torque ripple increases for all strategies in the two-phase-open interval. Table 4 reports 14.7% for the proposed controller without compensation and 17.0% for the conventional uncompensated case; with compensation, the values decrease to 8.5% and 14.1%, respectively. This result shows that the harmonic-reference layer is most beneficial in the more severe adjacent two-phase fault considered here.

4.5 Effective-Torque Analysis

Effective torque is evaluated as a 200-ms moving average, equivalent to ten periods at 50 Hz. Figure 5 and Table 3 summarize the three operating intervals.

Under one open phase, compensation raises the proposed-controller effective torque from 4.91 to 5.76 kN·m. For the conventional controller, the corresponding change is from 4.25 to 4.91 kN·m. Under two adjacent open phases, compensation changes the proposed result from 3.70 to 4.68 kN·m and the conventional result from 2.94 to 3.60 kN·m.

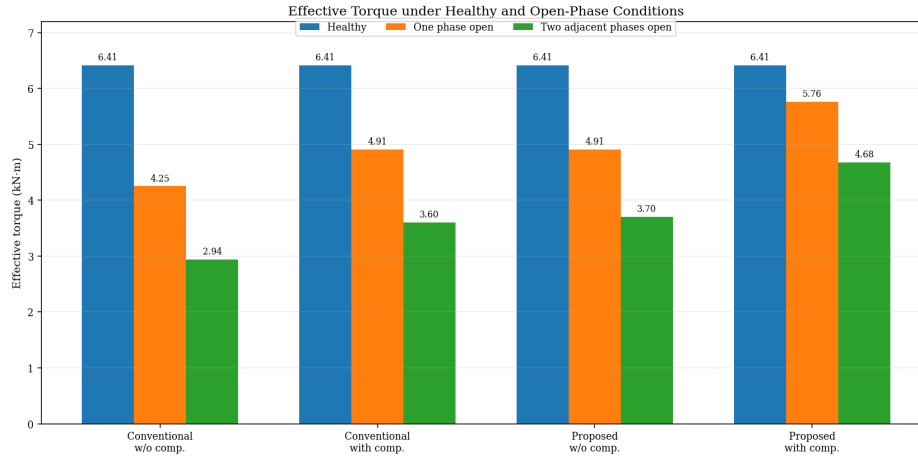
These changes are reported as absolute and relative torque recovery, rather than as “compensation efficiency,” because that phrase can be confused with electromechanical efficiency. The electrical efficiency of the complete drive would require a consistent input–output loss accounting that is outside the present torque-focused simulation comparison.

The comparison therefore supports the claimed fault-tolerant torque-retention advantage only within the specified simulations; it does not establish hardware-independent runtime superiority or statistical significance.

The improved post-fault response is consistent with the structure in Section 3: the estimator updates the predictive model, and the upper layer supplies harmonic-current references that are tracked together with torque by the ENMPC.

Table 3: Effective torque (kN·m) under healthy and open-phase conditions

Control strategy	Healthy (kN·m)	1-Phase open (kN·m)	2-Phase open (kN·m)	Average (kN·m)	Reduction (%)
Conventional w/o comp.	6.41	4.25	2.94	4.40	43.3
Conventional with comp.	6.41	4.91	3.60	4.83	32.2
Proposed (ENMPC) w/o comp.	6.41	4.91	3.70	5.04	33.7
Proposed (ENMPC) with comp.	6.41	5.76	4.68	5.48	17.7

**Figure 5:** Effective torque comparison under healthy, one-phase-open, and adjacent two-phase-open conditions. Values are identical to those in Table 3.

4.6 Torque-Ripple Analysis

Torque ripple is an important criterion for evaluating the performance quality of electric motors. The variations and comparison of torque ripple are shown in Figure 6 and Table 4.

For the proposed controller with compensation, the torque-ripple factor is 2.3% in the healthy state, 4.8% with one phase open, and 8.5% with two adjacent phases open; the corresponding average reported in Table 4 is 5.2%. For the conventional controller with compensation, the corresponding values are 2.9%, 7.8%, and 14.1%, with an average of 8.26%. In the uncompensated cases, the proposed and conventional averages are 8.1% and 10.0%, respectively. These tabulated values are taken as the numerical reference for the discussion.

When one or more stator phases are opened, the phase-current distribution becomes asymmetric and the electromagnetic system becomes unbalanced. This unbalance generates additional harmonic components in the torque. These harmonics originate from:

- uneven current distribution in the remaining phases;
- the creation of negative- and zero-sequence components;
- changes in the magnetic flux distribution.

Across the simulated fault intervals, the proposed compensated controller therefore produces the lowest tabulated torque-ripple factors. The comparison is descriptive and is not labeled statistically significant, because only one deterministic simulation realization is available.

Table 4: Torque-ripple factor (%) under healthy and open-phase conditions

Control strategy	Healthy state	1-Phase open	2-Phase open	Average
Conventional w/o comp.	3.1	9.9	17.0	10.0
Conventional with comp.	2.9	7.8	14.1	8.26
Proposed (ENMPC) w/o comp.	2.5	7.1	14.7	8.1
Proposed (ENMPC) with comp.	2.3	4.8	8.5	5.2

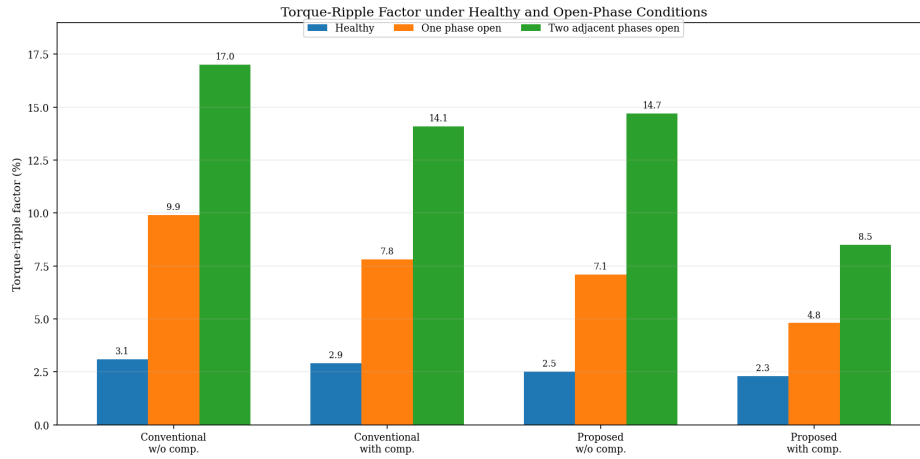


Figure 6: Torque-ripple factor comparison under healthy, one-phase-open, and adjacent two-phase-open conditions. Values are identical to those in Table 4.

4.7 Context Relative to Recent Fault-Tolerant Predictive Control

The numerical results in Tables 3 and 4 are internal comparisons on a common 1-MW seven-phase plant and should not be numerically pooled with published six-, five-, or nine-phase experiments. Nevertheless, the mechanism-level comparison in Table 1 is informative. Virtual-voltage-vector MPC [9] and enhanced natural fault-tolerant MPCC [17] reduce post-fault secondary-current distortion through converter-vector synthesis, whereas the present ENMPC treats the harmonic currents as explicit tracked states with references supplied by the slower optimizer. Online harmonic generation [22] solves the complementary reference-selection problem but does not impose the present state, voltage, and terminal-set constraints.

The 2025 model-free predictive approach in [3] represents a different design philosophy: it reduces plant-parameter dependence through an ultra-local model and disturbance estimation. The present controller retains the fault-coupled seven-phase state model because the associated cross-subspace structure is used directly in feasibility, current/voltage constraint enforcement, and the terminal stability argument. The comparison therefore supports a methodological distinction rather than a cross-platform claim of universal numerical superiority.

5 Conclusion, Limitations, and Future Work

This study formulated a hierarchical fault-tolerant controller for a seven-phase induction motor, in which an EKF/WRLS estimation layer updates harmonic references and an ENMPC regulates torque together with the third- and fifth-harmonic current subspaces. The open-phase models were expressed explicitly through phase-current projection matrices, and the ENMPC was supplemented with terminal cost and terminal-set conditions that provide nominal recursive feasibility and local asymptotic stability under the stated assumptions. In the MATLAB/Simulink study, the compensated proposed controller maintained 5.76 kN·m under one open phase and 4.68 kN·m under two adjacent open phases, with torque-ripple factors of 4.8% and 8.5%, respectively.

1. The numerical comparison indicates improved torque retention and ripple suppression relative to the conventional simulated baselines, particularly in the adjacent two-phase fault. As noted in Section 4.1, these are deterministic scenario metrics.
2. The scope of the present evidence is defined by five technical boundaries. First, validation in this paper is numerical, with hardware-in-the-loop and experimental implementation treated as subsequent hardware qualification. Second, the fault instants and faulted phases are prescribed, so fault detection/localization is outside the controller contribution. Third, Section 3.5 specifies the 0.5-ms execution deadline and the online problem dimension; processor-specific timing is an implementation-platform metric rather than a transferable MATLAB performance number. Fourth, the fault set contains one open phase and two adjacent open phases. Fifth, EKF/WRLS convergence is governed by the local observability, covariance, and persistence-of-excitation conditions stated in Section 3.2.1.
3. The stability statement is correspondingly limited to the feasible region and the terminal-set assumptions of Section 3.4. Under bounded estimator/model mismatch, the argument supports practical boundedness; it should not be interpreted as a global robustness guarantee.

Future work should therefore proceed in four measurable stages: hardware-in-the-loop timing and solver validation; experimental tests on a scaled seven-phase prototype; extension to non-adjacent, three-phase-open, and inter-turn short-circuit faults; and co-design of a fault-detection/localization module with the predictive controller. A further benchmark against model-free predictive control and learning-based fault-tolerant controllers would clarify the trade-off between model dependence, computational cost, and disturbance robustness.

These extensions are required before claims concerning industrial deployment, lifetime improvement, economic benefit, or autonomous operation can be made. The present contribution is therefore confined to the mathematical formulation and simulation-based performance of the hierarchical controller under the explicitly studied open-phase scenarios.

Prior-work boundary. Heidari et al. [11] supplies the previously published electromagnetic-thermal 1-MW motor design only. The fault-constrained model, estimator/optimizer, ENMPC formulation, stability analysis, and results in sections 2,3 and 4 are developed for the present manuscript and are not presented as contributions of [11].

Declarations

Availability of Supporting Data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Funding

The authors received no specific funding for this research.

Conflict of Interest

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Authors' Contributions

Zargham Heydari: Conceptualization, methodology, mathematical modeling, software, simulation, formal analysis, investigation, visualization, and writing—original draft.

Hamed Gorginpour: Conceptualization, methodology, supervision, validation, control-system formulation, interpretation of results, project administration, and writing—review and editing. **Nariman Heidari:** Methodology, validation, formal analysis, technical review of the power-electronic and drive-system aspects, interpretation of results, and writing—review and editing. All authors reviewed and approved the final version of the manuscript and agreed to be accountable for the integrity of the work.

Artificial Intelligence Statement Artificial intelligence (AI) tools, including large language models, were used solely for language editing and improving the readability of the manuscript. AI tools were not used to generate research ideas, perform analyses, interpret results, or produce the scientific content of the study. All scientific conclusions and intellectual contributions were made exclusively by the authors.

Publisher's Note

The publisher remains neutral regarding jurisdictional claims in published maps and institutional affiliations.

References

- [1] Barrero, F., Durán, M. J. (2016). "Recent advances in the design, modeling, and control of multiphase machines—Part I". *IEEE Transactions on Industrial Electronics*, 63(1), 449–458. <https://doi.org/10.1109/TIE.2015.2447733>
- [2] Casadei, D., Dujic, D., Levi, E., Serra, G., Tani, A., Zarri, L. (2008). "General modulation strategy for seven-phase inverters with independent control of multiple voltage space vectors". *IEEE Transactions on Industrial Electronics*, 55(5), 1921–1932. <https://doi.org/10.1109/TIE.2008.918481>
- [3] Chen, C., Zhou, H., Ye, C., Tao, T. (2025). "Natural fault-tolerant model-free predictive flux control in five-phase PMSM drives under any-phase open-circuit fault". *IEEE Access*, 13, 31889–31898. <https://doi.org/10.1109/ACCESS.2025.3542591>
- [4] Chen, H., Allgöwer, F. (1998). "A quasi-infinite horizon nonlinear model predictive control scheme with guaranteed stability". *Automatica*, 34(10), 1205–1217. [https://doi.org/10.1016/S0005-1098\(98\)00073-9](https://doi.org/10.1016/S0005-1098(98)00073-9)
- [5] Duran, M. J., Barrero, F. (2016). "Recent advances in the design, modeling, and control of multiphase machines—Part II". *IEEE Transactions on Industrial Electronics*, 63(1), 459–468. <https://doi.org/10.1109/TIE.2015.2448211>
- [6] Frikha, M., Croonen, J., Deepak, K., Benomar, Y., El Baghdadi, M., Hegazy, O. (2023). "Multiphase motors and drive systems for electric vehicle powertrains: State of the art analysis and future trends". *Energies*, 16(2), 768. <https://doi.org/10.3390/en16020768>

- [7] Goncalves, P., Cruz, S., Mendes, A. M. S. (2022). "Fault-tolerant predictive current control of six-phase PMSMs with a single isolated neutral configuration". *Machines*, 10(12), 1152. <https://doi.org/10.3390/machines10121152>
- [8] González-Prieto, I., Durán, M. J., Aciego, J. J., Martín, C., Barrero, F. (2018). "Model predictive control of six-phase induction motor drives using virtual voltage vectors". *IEEE Transactions on Industrial Electronics*, 65(1), 27–37. <https://doi.org/10.1109/TIE.2017.2714126>
- [9] González-Prieto, I., Durán, M. J., Bermúdez, M., Barrero, F., Martín, C. (2020). "Assessment of virtual-voltage-based model predictive controllers in six-phase drives under open-phase faults". *IEEE Journal of Emerging and Selected Topics in Power Electronics*, 8(3), 2634–2644. <https://doi.org/10.1109/JESTPE.2019.2915666>
- [10] González-Prieto, I., Durán, M. J., García-Entrambasaguas, P., Bermúdez, M. (2020). "Field-oriented control of multiphase drives with passive fault tolerance". *IEEE Transactions on Industrial Electronics*, 67(9), 7228–7238. <https://doi.org/10.1109/TIE.2019.2944056>
- [11] Heidari, Z., Gorginpour, H., Shahparasti, M. (2022). "Optimal electromagnetic-thermal design of a seven-phase induction motor for high-power speed-control applications". *Scientia Iranica*, 29(5), 2480–2497. <https://doi.org/10.24200/sci.2021.547664028>
- [12] Levi, E. (2008). "Multiphase electric machines for variable-speed applications". *IEEE Transactions on Industrial Electronics*, 55(5), 1893–1909. <https://doi.org/10.1109/TIE.2008.918488>
- [13] Liu, H., Wang, D., Yi, X., Meng, F. (2021). "Torque ripple suppression under open-phase fault conditions in a five-phase induction motor with harmonic injection". *IEEE Journal of Emerging and Selected Topics in Power Electronics*, 9(1), 274–288. <https://doi.org/10.1109/JESTPE.2019.2952374>
- [14] Mayne, D. Q., Rawlings, J. B., Rao, C. V., Scokaert, P. O. M. (2000). "Constrained model predictive control: Stability and optimality". *Automatica*, 36(6), 789–814. [https://doi.org/10.1016/S0005-1098\(99\)00214-9](https://doi.org/10.1016/S0005-1098(99)00214-9)
- [15] Sun, X., Li, T., Tian, X., Zhu, J. (2022). "Fault-tolerant operation of a six-phase permanent magnet synchronous hub motor based on model predictive current control with virtual voltage vectors". *IEEE Transactions on Energy Conversion*, 37(1), 337–346. <https://doi.org/10.1109/TEC.2021.3109869>

- [16] Taheri, A., Ren, H.-P., Holakooie, M. H. (2020). "Sensorless loss model control of the six-phase induction motor in all speed range by Extended Kalman Filter". *IEEE Access*, 8, 118741–118750. <https://doi.org/10.1109/ACCESS.2020.2964828>
- [17] Wang, H., Zheng, X., Yuan, X., Wu, X. (2022). "Enhanced natural fault-tolerant model predictive current control in nine-phase motor drives under open-phase faults". *IEEE Transactions on Energy Conversion*, 37(4), 2449–2460. <https://doi.org/10.1109/TEC.2022.3179735>
- [18] Yang, G., Hussain, H., Li, S., Zhang, J., Yang, J. (2022). "Fault-tolerant control for multiphase induction machines with torque ripple reduction considering harmonic injection". *IEEE Transactions on Power Electronics*, 37(12), 14005–14010. <https://doi.org/10.1109/TPEL.2022.3188999>
- [19] Yang, G., Li, S., Hussain, H., Zhang, J., Yang, J. (2023). "A novel SVPWM fault-tolerant strategy for torque ripple reduction of seven-phase induction machines under single-phase open-circuit fault". *IEEE Transactions on Power Electronics*, 38(4), 5217–5229. <https://doi.org/10.1109/TPEL.2022.3232122>
- [20] Yepes, A. G., López, O., González-Prieto, I., Durán, M. J., Doval-Gandoy, J. (2022). "A comprehensive survey on fault tolerance in multiphase AC drives, Part 1: General overview considering multiple fault types". *Machines*, 10(3), 208. <https://doi.org/10.3390/machines10030208>
- [21] Yepes, A. G., González-Prieto, I., López, O., Durán, M. J., Doval-Gandoy, J. (2022). "A comprehensive survey on fault tolerance in multiphase AC drives, Part 2: Phase and switch open-circuit faults". *Machines*, 10(3), 221. <https://doi.org/10.3390/machines10030221>
- [22] Yepes, A. G., Shawier, A., Abdel-Azim, W. E., Abdel-Khalik, A. S., Ahmed, S., Doval-Gandoy, J. (2023). "General online current-harmonic generation for increased torque capability with minimum stator copper loss in fault-tolerant multiphase induction motor drives". *IEEE Transactions on Transportation Electrification*, 9(3), 4650–4667. <https://doi.org/10.1109/TTE.2023.3244742>

Authors' Bio-sketches

Zargham Heydari holds a Ph.D. in Electrical Engineering – Power. For years, he has served as a faculty member and Head of the Electrical Engineering Department at

Islamic Azad University, Khormoj Branch, and as a visiting lecturer at the Bushehr and Kazerun Branches. He has also held positions such as President of Islamic Azad University, Khormoj Branch, Director of the Research Office, and Head of the Electrical Engineering Department at Bushehr Branch. Since 2003, he has been a board member and CEO of Nariman Azma Company, and he is a Senior Grade member of the Construction Engineering Organization in the field of electrical installations. His research interests include induction motor control, multiphase machines, optimal electromagnetic-thermal design, predictive control, and fault-tolerant predictive control. Email: zargham.hidari@iaau.ac.ir

Hamed Gorginpour is an Associate Professor in the Faculty of Intelligent Systems Engineering and Data Science at Persian Gulf University, Bushehr. He has also served for years as Director of the Persian Gulf Science and Technology Park, Bushehr. He received his M.Sc. and Ph.D. in Electrical Power Engineering from Sharif University of Technology, Tehran. His research interests include induction motor control, doubly-fed machines, and wind generators. The main focus of Dr. Gorginpour's research is on the modeling, analysis, and control of advanced electrical machines and their applications in renewable energy systems, especially wind turbines.

Nariman Heidari holds a B.Sc. in Computer Engineering, Software Engineering major, with expertise in Python programming and the Django framework. He works in applied software development, web page design, and translation of specialized texts from English to Persian and vice versa. In addition to general programming skills, he has played an effective role in implementing computer programs related to electrical machine control. These programs include simulation, monitoring, and control of multiphase induction machines, design of application interfaces for analyzing electrical and thermal data, and implementation of advanced control algorithms such as Model Predictive Control (MPC) and Space Vector Pulse Width Modulation (SVPWM). He has also collaborated in developing software systems for the fault-tolerant predictive control and its applications in wireless sensor networks and power systems. His other activities include preparing custom software, designing scientific and research websites, and translating technical and specialized texts.