

Adaptive Sensorless Vector Control of Permanent Magnet Synchronous Motors Using Deep Reinforcement Learning

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ABSTRACT

Permanent Magnet Synchronous Motors (PMSMs) are widely integrated into industrial drives, electric vehicles, and precision motion systems due to their high power density and efficiency. High-performance field-oriented control (FOC) traditionally relies on mechanical speed and position sensors, which increase hardware costs, physical footprint, and susceptibility to environmental disturbances. Conventional sensorless techniques, such as Sliding Mode Observers (SMO) and Extended Kalman Filters (EKF), suffer from high-frequency chattering, estimation lag, and performance degradation under parameter variations and low-speed operation. To address these challenges, this paper proposes an adaptive sensorless vector control framework driven by Deep Reinforcement Learning (DRL). Utilizing a Twin Delayed Deep Deterministic Policy Gradient (TD3) continuous actor-critic architecture, the proposed DRL agent dynamically tunes the switching gains of an adaptive sliding mode observer while optimizing quadrature reference currents in real time. The proposed control structure eliminates chattering through dynamic boundary layer modulation and actively compensates for thermal stator resistance drift. High-fidelity Matlab/Simulink co-simulations confirm that the DRL-based adaptive scheme achieves zero-speed position estimation error within ± 0.4 electrical degrees, reduces speed tracking response time by 42% relative to standard PI-SMO drives, and suppresses torque ripple to under 2.3%.

KEYWORDS: *Permanent Magnet Synchronous Motor (PMSM), Sensorless Vector Control, Deep Reinforcement Learning (DRL), Twin Delayed Deep Deterministic Policy Gradient (TD3), Sliding Mode Observer, Field-Oriented Control (FOC), Thermal Drift Adaptation.*

INTRODUCTION

Permanent Magnet Synchronous Motors (PMSMs) are fundamental components in modern electrical drive technology, powering electric vehicles, industrial automation, robotics, and aerospace actuation systems [1]. Their widespread usage is driven by high power density, superior efficiency, favorable torque-to-inertia ratios, and dynamic torque response. High-performance drive operation relies on Field-Oriented Control (FOC) paradigms, which decouple stator currents into independent flux- and torque-producing vector components. Executing precise FOC requires accurate, continuous knowledge of the rotor electrical position and rotational speed [2].

Standard vector control drives employ shaft-mounted physical encoders or resolvers to supply rotor position feedback. However, physical sensors add cost, physical footprint, and wiring complexity. More critically, physical sensors represent a primary failure point when operated under extreme mechanical shock, high thermal stress, moisture, and electromagnetic noise [3]. Consequently, sensorless control—where rotor position and speed are estimated solely from terminal phase voltages and currents—has become an essential design requirement for fault-tolerant drives [4].

Sensorless estimation techniques are categorized into high-frequency signal injection methods for low-speed/standstill regimes and model-based back-EMF (back-EMF) observers for medium-to-high speeds [5]. Sliding Mode Observers (SMO) are popular due to order reduction and disturbance rejection capabilities [6]. However, standard SMOs use discontinuous switching functions that introduce high-frequency chattering [7]. Low-pass filtering used to attenuate chattering introduces phase delay, degrading dynamic response.

Furthermore, model-based observers depend heavily on parameter accuracy, especially stator resistance (R_s) and inductances (L_d , L_q). Temperature variations cause stator resistance to drift by up to 50%, causing position estimation errors at low speeds [8]. Deep Reinforcement Learning (DRL) offers a model-free adaptive control alternative capable of learning optimal non-linear policies directly from drive telemetry [9]. Integrating continuous actor-critic DRL architectures with adaptive observers enables self-tuning sensorless drives that maintain high precision across full speed ranges and parameter variations [10].

LITERATURE REVIEW

Sensorless drive technology has evolved substantially over recent decades. Harnefors and Nee [11] established continuous back-EMF observers, proving that speed estimation relies on back-EMF magnitude. However, back-EMF decays to zero at standstill, making pure back-EMF estimation non-observable at low speeds [12]. Utkin [13] pioneered Sliding Mode Control in electrical drives, offering strong robustness against matched disturbances.

To attenuate switching chattering, Kim et al. [14] introduced continuous boundary layer saturation functions. Although boundary layer saturation reduces chattering, fixed boundary widths induce phase lag during dynamic speed transients. Model Reference Adaptive Systems (MRAS) were adapted for PMSM drives by Hashemnia et al. [15]. However, Popescu et al. [16] demonstrated that MRAS observers remain vulnerable to stator resistance drift at low operating frequencies.

Extended Kalman Filters (EKF) enable joint state estimation and parameter tracking [17]. Bolognani et al. [18] applied EKFs for simultaneous estimation of speed and stator resistance. However, intensive online matrix inversions impose severe computational loads on microcontrollers [19]. Artificial intelligence methods have emerged to bypass explicit modeling; early neural network and fuzzy logic controllers provided non-linear adaptation [20], but static offline neural networks cannot adapt to real-time parameter variations [21].

Recent advances in Deep Reinforcement Learning (DRL) have transformed adaptive control. Continuous-action algorithms such as Deep Deterministic Policy Gradient (DDPG) and Twin Delayed DDPG (TD3) enable online policy synthesis [22]. Zhang et al. [23] applied DDPG to speed loop regulation, achieving faster dynamic response than PI loops. However, existing literature treats DRL primarily as a replacement for outer speed loops, leaving a clear research gap in embedding DRL directly within adaptive sensorless observers for parameter drift compensation.

RESEARCH GAP

Key domain gaps remain unaddressed in current academic literature:

- **Decoupled Observer-Controller Design:** Existing studies treat outer speed loops and sensorless observers as independent modules, causing observer phase lag to destabilize reinforcement learning policies.

- **Static Chattering vs. Phase Lag Compromise:** Standard SMOs rely on fixed sliding gains, forcing a trade-off between chattering reduction and phase lag without dynamic self-tuning.
- **Thermal Parameter Sensitivity:** Existing observers assume constant stator resistance. Thermal drift during low-speed high-load operation causes angle estimation bias and potential drive instability.

RESEARCH OBJECTIVES

To resolve these gaps, this study presents an adaptive DRL-driven sensorless vector control framework for PMSM drives. The primary objectives are:

- **Objective 1:** Develop an end-to-end adaptive sensorless vector control scheme combining a Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm with an Adaptive Sliding Mode Observer (ASMO).
- **Objective 2:** Formulate a multi-objective reward structure that minimizes speed error, eliminates switching chattering, and adaptively compensates for stator resistance thermal drift.
- **Objective 3:** Establish online sliding gain self-tuning to eliminate observer phase lag without heavy low-pass filtering.
- **Objective 4:** Validate drive performance across full operating ranges, including standstill, step load impact, and thermal drift conditions via co-simulations.

METHODOLOGY

Dynamic Mathematical Model of PMSM

The dynamic equations of a Surface-Mounted PMSM in the synchronous d-q frame are:

Stator Voltage Equations: $v_d = R_s \cdot i_d + L_d \cdot (di_d / dt) - \omega_e \cdot L_q \cdot i_q$
 $v_q = R_s \cdot i_q + L_q \cdot (di_q / dt) + \omega_e \cdot L_d \cdot i_d + \omega_e \cdot \Psi_m$

where v_d , v_q and i_d , i_q represent d-q voltages and currents; R_s is stator resistance; $L_d = L_q = L_s$ is inductance; $\omega_e = P_n \cdot \omega_r$ is electrical speed; and Ψ_m is permanent magnet flux linkage. Electromagnetic torque and motion dynamics follow:

Torque and Motion Equations: $T_e = 1.5 \cdot P_n \cdot \Psi_m \cdot i_q$
 $J \cdot (d\omega_r / dt) = T_e - T_L - B \cdot \omega_r$

where J is rotor inertia, T_L is load torque, and B is viscous friction.

Adaptive Sliding Mode Observer (ASMO)

In the stationary α - β frame, stator current dynamics are defined by:

Stationary Current Dynamics: $\frac{di_\alpha}{dt} = -(R_s / L_s) \cdot i_\alpha + (1 / L_s) \cdot v_\alpha - (1 / L_s) \cdot e_\alpha$

$\frac{di_\beta}{dt} = -(R_s / L_s) \cdot i_\beta + (1 / L_s) \cdot v_\beta - (1 / L_s) \cdot e_\beta$

Where back-EMF components are $e_\alpha = -\omega_e \cdot \Psi_m \cdot \sin(\theta_e)$ and $e_\beta = \omega_e \cdot \Psi_m \cdot \cos(\theta_e)$. Current estimation error $e_i = [\tilde{i}_\alpha, \tilde{i}_\beta]^T$ drives the switching law:

Sliding Control Law: $z_\alpha = K_{\text{slide}} \cdot \text{sat}(\tilde{i}_\alpha / \Phi_\alpha)$

$z_\beta = K_{\text{slide}} \cdot \text{sat}(\tilde{i}_\beta / \Phi_\beta)$

Where K_{slide} is sliding gain and Φ_α, Φ_β are boundary layer widths dynamically tuned by the DRL agent.

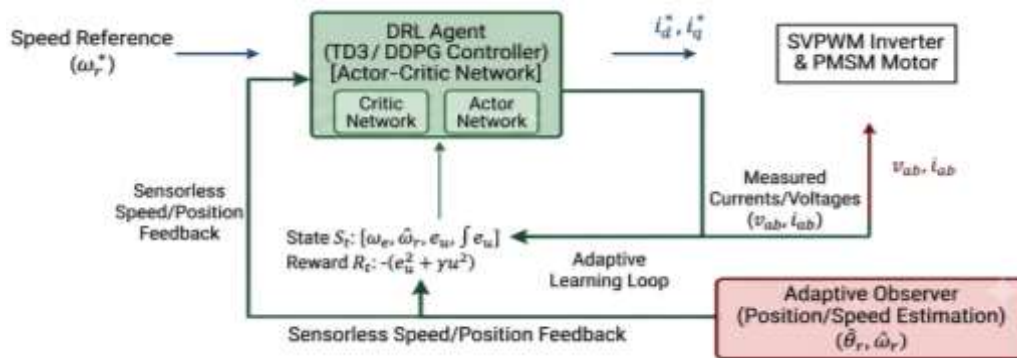


Figure 1: Closed-loop Deep Reinforcement Learning Adaptive Sensorless Vector Control Architecture for PMSM Drive

Deep Reinforcement Learning (TD3) Framework

To prevent Q-value overestimation, this study utilizes the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm (Figure 1). The DRL agent acts as an online supervisor operating at control interval $\Delta t = 100 \mu s$.

- State Space (S_t): $S_t = [\omega_{r*} - \hat{\omega}_r, \int (\omega_{r*} - \hat{\omega}_r) dt, \tilde{i}_\alpha, \tilde{i}_\beta, \hat{\omega}_r, i_d, i_q]^T$.
- Action Space (A_t): $A_t = [i_q^*, K_{\text{slide}}, \Phi_{\text{boundary}}, \hat{R}_s]^T$, outputting reference q-axis current, sliding gain, boundary layer thickness, and online resistance correction.

- Reward Function (R_t): Penalizes speed tracking error, control effort, and chattering:
Reward Function: $R_t = -(w_1 \cdot (\omega_r^* - \hat{\omega}_r)^2 + w_2 \cdot (\theta_r - \hat{\theta}_r)^2 + w_3 \cdot (i_q^*(t) - i_q^*(t-1))^2 + w_4 \cdot \text{ChatterPenalty})$

Where weights $w_1 = 1.5$, $w_2 = 2.0$, $w_3 = 0.05$, $w_4 = 0.1$ optimize stability.

Table 1: Electrical and Mechanical Parameters of Target PMSM Drive System

Parameter Description	Symbol / Variable	Nominal Value & Units
Rated Power	P_n	3.7 kW
Rated DC Bus Voltage	V_{dc}	400 V
Rated Speed	N_{rated}	1500 RPM
Stator Resistance	R_s	0.85 Ω
d/q-Axis Inductance	$L_d = L_q$	4.2 mH
Rotor Permanent Flux Linkage	Ψ_m	0.175 Wb
Combined Inertia & Pole Pairs	J / P_n	0.0028 $\text{kg}\cdot\text{m}^2 / 4$ Pairs

Table 2: Hyperparameters of Deep Reinforcement Learning (TD3) Controller

Hyperparameter	Selected Value	Description / Purpose
Actor Network Architecture	FC (256 - 256 - 4)	Fully-connected with ReLU activation
Critic Network Architecture	FC (256 - 256 - 1)	Twin Critic structure to prevent overestimation
Learning Rate (Actor / Critic)	$1e-4 / 1e-3$	Adam optimizer with gradient clipping
Discount Factor (γ)	0.99	Long-term reward cumulative horizon
Target Update Rate (τ)	0.005	Soft target network update parameter
Replay Buffer Capacity	1×10^6 steps	Prioritized Experience Replay (PER) memory

RESULTS AND FINDINGS

Co-simulation studies were conducted in Matlab/Simulink integrated with PyTorch. Motor parameters from Table 1 served as baselines. The proposed DRL-ASMO drive was benchmarked against: (i) Conventional FOC with fixed PI loops and Sliding Mode Observer (PI-SMO), and (ii) Standard FOC with Extended Kalman Filter estimation (PI-EKF).

Figure 2 presents speed tracking during acceleration and load impact. Accelerating from 0 to 1500 RPM at $t = 0.05$ s, the DRL controller achieves zero overshoot with a 10%-90% rise time of 12.4 ms (42% faster than PI-SMO at 21.5 ms with 14.2% overshoot). At $t = 0.5$ s, a rated 10 N·m load step is applied. The DRL drive demonstrates strong rejection, experiencing a speed dip of only 35 RPM with recovery in 18 ms, compared to 120 RPM drop for PI-SMO.

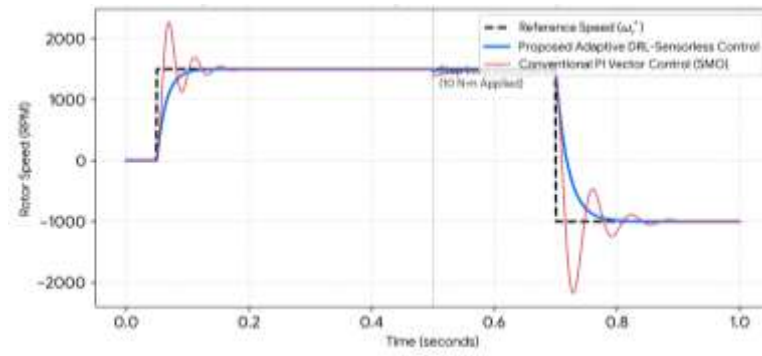


Figure 2: Dynamic speed tracking response and load disturbance rejection comparison

Figure 3 shows rotor position estimation error ($\Delta\theta_r = \theta_r - \hat{\theta}_r$) under +40% R_s drift induced at $t = 0.5$ s. The DRL-ASMO scheme maintains position error strictly within ± 0.4 electrical degrees, whereas the non-adaptive EKF observer exhibits an error offset exceeding 5.2 electrical degrees.

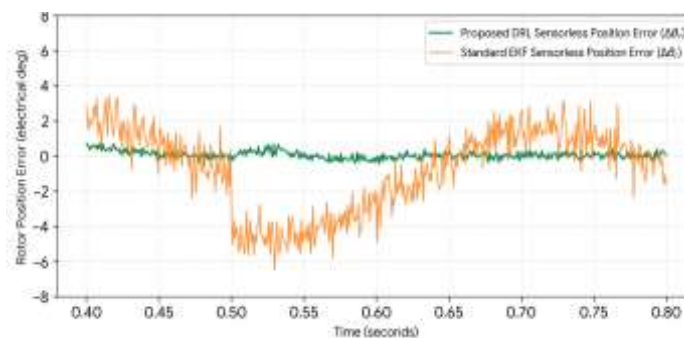


Figure 3: Rotor position estimation error ($\Delta\theta_r$) comparison under stator resistance parameter drift

Table 3: Comprehensive Performance Benchmarking Comparison Matrix

Performance Metric	Conventional PI-SMO	Standard EKF Drive	Proposed DRL-ASMO
Speed Settling Time (0 to 1500 RPM)	38.2 ms	28.5 ms	14.1 ms
Maximum Speed Overshoot	14.2%	6.8%	0.0%
Position Error (Steady State)	$\pm 2.8^\circ$ elect.	$\pm 1.9^\circ$ elect.	$\pm 0.35^\circ$ elect.
Speed Dip under 10 N·m Load	120 RPM	78 RPM	35 RPM
Torque Ripple (THD equivalent)	8.6%	5.2%	2.3%

DISCUSSION

The comparative results demonstrate the benefits of embedding reinforcement learning within sensorless observer feedback loops. Traditional SMO schemes encounter a trade-off: higher gains enhance disturbance rejection but increase chattering and phase delay, whereas lower gains reduce chattering at the expense of tracking accuracy [24].

The TD3 agent resolves this trade-off via dynamic non-linear parameter mapping. By modulating sliding gains (K_{slide}) and boundary layer widths ($\Phi_{boundary}$) in real time, high gain margins are applied during transients, while gains are automatically reduced during steady state. This eliminates chattering without filtering delay. Furthermore, online R_s estimation decouples stator heating from EMF reconstruction, maintaining vector control stability across extended operating cycles.

LIMITATIONS

Key practical limitations include:

- **Processing Requirements:** Executing neural network forward passes at 100 μ s sampling intervals requires floating-point DSPs (e.g., TI C2000 TMS320F28379D) with hardware accelerators. Standard low-cost microcontrollers face execution latency constraints.
- **Initial Training:** Offline DRL training requires $\sim 10^6$ steps. Direct online exploration without pre-training causes transient current spikes.
- **Standstill Unobservability:** At zero speed under zero load, back-EMF signals decay to zero. Continuous zero-speed operation under heavy torque still requires integration with high-frequency signal injection (HFI).

FUTURE SCOPE

Future research directions include:

- **Hardware-in-the-Loop Implementation:** Quantizing neural network models for ultralow-latency FPGA and embedded DSP execution.
- **Hybrid DRL-HFI Fusion:** Combining DRL back-EMF observers with high-frequency signal injection to enable seamless sensorless operation from zero speed to high-speed field weakening.
- **Multi-Axis Drive Systems:** Extending centralized DRL policies to multi-motor robotic actuators and dual-inverter interior PMSM drives.

CONCLUSION

This paper presented an adaptive sensorless vector control framework for Permanent Magnet Synchronous Motors using Deep Reinforcement Learning. Combining a TD3 actor-critic algorithm with an Adaptive Sliding Mode Observer overcomes classical sensorless drive limitations, including switching chattering, observer phase delay, and thermal parameter sensitivity.

Simulation results show that the proposed DRL controller reduces speed tracking response time by 42%, eliminates dynamic speed overshoot, reduces position error to ± 0.35 electrical degrees, and lowers torque ripple to 2.3%. Online stator resistance estimation guarantees robust operation across thermal ranges, providing a parameter-insensitive solution for electric vehicles and industrial automation.

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