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Fractional-Order Hybrid Observer Architecture for Intelligent Sensorless Control of UAV Propulsion Systems: Integrating High-Frequency Injection with Adaptive Fractional Kalman Filtering

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Abstract

This paper presents a novel fractional-order hybrid observer framework for robust sensorless control of brushless DC (BLDC) motor drives in unmanned aerial vehicle (UAV) propulsion systems, addressing the fundamental limitations of conventional integer-order observers through the lens of fractional calculus. The proposed architecture synergistically integrates high-frequency square-wave signal injection for zero/low-speed operation with an adaptive fractional-order extended Kalman filter (AFEKF) augmented by online stator resistance and flux linkage estimation, capitalizing on the memory and hereditary properties inherent to fractional-order systems. A minimum-order current observer enables accurate three-phase current reconstruction using a single DC-link sensor, substantially reducing hardware complexity and cost. The complete algorithm is implemented on an STM32H7 microcontroller and experimentally validated on a 1.5 kW drone propulsion testbench and in-flight platform. Results demonstrate reliable startup under 50% rated load, stable operation from standstill to 5000 RPM on the UAV motor (and validated up to 22,000 RPM on a high-speed test motor, $<4^\circ$ electrical position error at 5 kRPM, and strong robustness against 35% stator resistance variation. In-flight tests confirm improved thrust smoothness and hover stability compared to conventional sensorless strategies. The proposed fractional-order architecture offers a practical, resilient, and computationally feasible solution for next-generation autonomous aerial systems, establishing a new paradigm for observer design in electric propulsion.

Keywords: sensorless control; brushless DC (BLDC) motor; fractional-order extended Kalman filter; high-frequency injection; fractional calculus; parameter estimation; minimum-order observer; unmanned aerial vehicles (UAV); fractional-order systems; hybrid observer



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1. Introduction

Unmanned aerial vehicles (UAVs) have emerged as transformative platforms across civilian, commercial, and defense sectors, with their operational capabilities fundamentally constrained by the performance of onboard electric propulsion systems. Contemporary multirotor aerial platforms demand propulsion architectures that simultaneously satisfy stringent requirements in thrust density, energy efficiency, transient response, and operational reliability. The propulsion system's performance directly dictates hover stability,

trajectory tracking accuracy, disturbance rejection capability, and mission endurance parameters that collectively define the operational envelope of autonomous aerial systems [1–4].

Brushless DC (BLDC) motors, commonly modeled as surface-mounted permanent magnet synchronous machines (SPMSMs), have become the dominant actuation solution for UAV propulsion due to their superior torque-to-weight ratio, high efficiency, structural robustness, and minimal maintenance requirements. To fully exploit these electromechanical advantages, modern UAV propulsion systems employ field-oriented control (FOC), which enables decoupled regulation of torque- and flux-producing current components, providing superior dynamic performance compared to conventional six-step commutation strategies [5,6]. However, conventional FOC implementations depend on mechanical rotor position sensors such as encoders or Hall-effect devices. While these sensors provide accurate position feedback, they introduce additional weight, wiring complexity, electromagnetic interference vulnerability, and single-point failure risks—particularly problematic in aerial platforms exposed to vibration, temperature gradients, and harsh environmental conditions [7,8]. These limitations have motivated extensive research into sensorless control strategies that eliminate mechanical sensors while maintaining or exceeding closed-loop performance.

Back-electromotive force (back-EMF) based methods constitute the most widely adopted class of sensorless techniques. Approaches including sliding-mode observers (SMO), Luenberger observers, model reference adaptive systems (MRAS), and extended Kalman filters (EKF) demonstrate high estimation accuracy at medium and high speeds where the back-EMF amplitude is sufficiently large [9–13]. Among these, the EKF provides statistically optimal estimation under Gaussian noise assumptions and has been extensively investigated for PMSM drives [14–16]. Nevertheless, all back-EMF-based techniques fundamentally suffer from degraded observability as the rotor speed approaches zero. At standstill, the back-EMF term vanishes, leading to rank deficiency in the observability matrix and rendering position estimation unreliable [17,18]. This limitation is critical for UAV applications, where reliable startup under load, low-speed hovering, and precision maneuvering are mandatory operational requirements.

To overcome the low-speed observability challenge, high-frequency signal injection (HFSI) methods exploit rotor magnetic saliency to extract position information independent of back-EMF [19–22]. By injecting a high-frequency voltage component and analyzing the current response, the rotor position can be estimated even at standstill. Square-wave injection techniques have gained attention due to their implementation simplicity and compatibility with digital PWM platforms [23,24]. However, pure HFSI strategies are not optimal across the entire speed range due to increased signal processing requirements, injection-induced losses, and potential acoustic noise. Consequently, hybrid observer architectures combining low-speed saliency-based estimation with high-speed back-EMF-based observers have been proposed [25–27]. Despite promising results, seamless transition mechanisms and stability guarantees remain open challenges in many reported implementations, with conventional integer-order observer structures exhibiting limited adaptability to the complex, non-integer dynamics inherent in electromechanical systems.

A major limitation of model-based observers lies in parameter sensitivity. Stator resistance and permanent magnet flux linkage vary significantly with temperature rise and magnetic saturation during flight operation. Parameter mismatch introduces steady-state estimation bias and can degrade dynamic performance [28,29]. Adaptive EKF structures that augment the state vector with parameter estimation have been investigated; however, their embedded implementation complexity and real-time feasibility for UAV-class microcontrollers require further validation [30,31]. Additionally, conventional integer-order Kalman filters, while effective, do not fully capture the fractional-order dynamics present in

thermal processes, magnetic hysteresis, and material relaxation phenomena that influence motor parameters during operation.

In addition to estimation robustness, hardware simplification is increasingly important in aerial systems. Conventional FOC typically requires two or three phase current sensors. Single-shunt current reconstruction techniques have been explored to reduce cost and the PCB footprint, yet many approaches suffer from bandwidth limitations or switching-state dependency issues [32,33]. A unified architecture integrating robust hybrid position estimation with single-sensor current reconstruction has not been comprehensively demonstrated for high-power UAV propulsion platforms under both laboratory and in-flight conditions.

Recent advances in fractional calculus have opened new frontiers in control systems and state estimation, offering powerful mathematical tools to model systems with memory effects, hereditary properties, and non-integer order dynamics [34–36]. Fractional-order Kalman filters, in particular, have demonstrated superior performance in handling systems with long-range dependencies, anomalous diffusion processes, and complex noise characteristics that conventional integer-order filters cannot adequately address [37,38]. The application of fractional-order estimation techniques to electric motor drives remains largely unexplored, despite the inherent fractional dynamics present in thermal processes affecting stator resistance, magnetic hysteresis phenomena influencing flux linkage, and the viscoelastic behavior of motor materials under mechanical stress [39,40]. The integration of fractional-order estimation with hybrid sensorless control architectures presents a promising yet underexplored research direction for enhancing robustness and adaptability in UAV propulsion systems.

Therefore, a research gap remains in the development of a practical, full speed-range, parameter-adaptive, sensor-minimized observer architecture that leverages fractional-order estimation principles and is validated under realistic aerial operating conditions. The inherent fractional dynamics of motor thermal behavior, magnetic hysteresis, and mechanical stress response suggest that fractional-order observers could provide superior estimation accuracy and robustness compared to conventional integer-order approaches.

To address the aforementioned challenges, this paper proposes a robust fractional-order hybrid sensorless control framework tailored for UAV propulsion drives. The key contributions are:

Fractional-Order Hybrid Observer: Integration of high-frequency square-wave injection for zero/low-speed operation with an adaptive fractional-order extended Kalman filter (AFEKF) for medium-to-high-speed estimation, ensuring continuous observability from standstill to 22,000 RPM while exploiting the memory properties of fractional calculus for enhanced estimation accuracy.

Fractional-Order Parameter Identification: Augmentation of the AFEKF state vector to include stator resistance and permanent magnet flux linkage, enabling real-time adaptation to thermal variation through fractional-order update laws that better capture the non-integer dynamics of temperature-dependent parameters, maintaining estimation accuracy under 35% parameter drift.

Single-Shunt Current Reconstruction: Implementation of a minimum-order observer with fractional-order correction terms to reconstruct three-phase currents from a single DC-link current sensor, reducing hardware complexity without compromising FOC bandwidth.

Stability-Assured Transition Mechanism: A hysteresis-based switching strategy with state initialization guarantees bounded estimation error and bumpless observer transition, with fractional-order stability analysis ensuring robust convergence.

Comprehensive Experimental and In-Flight Validation: Validation on a 1.5 kW propulsion testbench and quadcopter flight platform, demonstrating improved startup reliability,

reduced speed ripple, enhanced dynamic response, and superior robustness against parameter variation compared to conventional integer-order approaches.

The remainder of this paper is organized as follows: Section 2 presents the mathematical modeling of the BLDC motor and reviews the state of the art in sensorless control, with particular emphasis on fractional-order estimation techniques. Section 3 details the proposed fractional-order hybrid observer design, including the AFEKF formulation and seamless transition strategy. Section 4 describes the minimum-order current observer for single-shunt reconstruction. Section 5 presents the experimental setup and implementation details. Section 6 reports and discusses the experimental results, including comparative analysis with conventional methods and in-flight validation. Section 7 concludes the paper and outlines directions for future research.

2. Mathematical Modeling and State of the Art

2.1. BLDC Motor Model in the Synchronous Reference Frame

For the purpose of FOC, the BLDC motor is mathematically modeled as a three-phase permanent magnet synchronous motor (PMSM). The model in the synchronous rotating (d-q) reference frame, which rotates in synchronism with the rotor flux, is given by the following voltage equations:

$$V_d = R_s i_d + L_d \frac{di_d}{dt} - \omega_e L_q i_q \quad (1)$$

$$V_q = R_s i_q + L_q \frac{di_q}{dt} - \omega_e L_d i_d + \omega_e \lambda_m \quad (2)$$

where:

- v_d, v_q are the d- and q-axis stator voltages,
- i_d, i_q are the d- and q-axis stator currents,
- R_s is the stator phase resistance,
- L_d, L_q are the d- and q-axis stator inductances,
- ω_e is the electrical angular velocity ($\omega_e = (P/2) \omega_m$, where P is the number of poles and ω_m is the mechanical angular velocity),
- λ_m is the flux linkage established by the permanent magnets.

For surface-mounted BLDC motors (SPMSM), the d- and q-axis inductances are approximately equal ($L_d \approx L_q$). The electromagnetic torque T_e is produced by the interaction of the rotor flux and the stator current components and is expressed as:

$$T_e = \left(\frac{3P}{4}\right) [\lambda_m i_q + (L_d - L_q) i_d i_q] \quad (3)$$

Under the common $i_d = 0$ control strategy, which maximizes torque per ampere for SPMSMs, the torque equation simplifies to:

$$T_e = \frac{3}{2} \frac{P}{2} \lambda_m i_q = K_t i_q \quad (4)$$

where K_t is the motor torque constant. The mechanical equation of motion is:

$$T_e - T_L - B \omega_m = J \frac{d\omega_m}{dt} \quad (5)$$

where T_L is the load torque, B is the viscous friction coefficient, and J is the moment of inertia of the rotor and load.

2.2. Review of Sensorless Techniques

A vast body of literature exists on sensorless control for PMSMs/BLDC motors. This review focuses on the most relevant techniques for drone applications.

Back-EMF Based Methods at Medium/High Speeds:

Sliding-Mode Observer (SMO): SMOs are popular due to their inherent robustness to parameter variations and disturbances [7,13]. A discontinuous switching function forces the estimated currents to converge to the measured currents. The equivalent control signal required to maintain this sliding motion contains information about the back-EMF, from which the rotor position is derived. A major drawback is the inherent “chattering” phenomenon, which is typically mitigated using low-pass filters, albeit at the cost of introduced phase lag that must be compensated.

Extended Kalman Filter (EKF): The EKF is a recursive stochastic state estimator for nonlinear systems [9,14]. It provides an optimal estimate of the system states (e.g., currents, speed, position) by minimizing the mean square estimation error. It excels at handling the system and measuring noise. However, its performance is heavily dependent on the accuracy of the system model and the chosen noise covariance matrices (Q and R). It is also computationally intensive, which can be a constraint for low-cost microcontrollers.

Saliency-Tracking Methods for Low/Zero Speed: High-Frequency Signal Injection (HFSI): These methods are active techniques that are independent of the back-EMF [10]. A high-frequency voltage signal (sinusoidal or square wave) is superimposed on the fundamental excitation. The resulting high-frequency current response is modulated by the rotor position due to magnetic saliency. By demodulating this current response, the rotor position can be extracted. Techniques include rotating vector injection [16] and pulsating vector injection in the estimated d-axis [17]. The main challenge is the requirement for signal processing (band-pass filtering, synchronous demodulation) and the potential for audible noise and additional losses.

Hybrid and Adaptive Methods: Recognizing the complementary strengths of different methods, several researchers have proposed hybrid observers [18,19]. These typically switch between a low-speed method (like HFSI) and a high-speed method (like SMO or EKF). The challenge lies in ensuring a smooth and bumpless transition between the observers.

To address parameter sensitivity, online parameter identification schemes have been integrated with observers. Methods include Model Reference Adaptive Systems (MRAS) [20] and recursive least squares (RLS) algorithms. Integrating these directly into an EKF framework by augmenting the state vector is an elegant but computationally demanding solution [22].

The proposed method in this paper builds upon these concepts to create a unified, robust, and practical solution tailored for the stringent requirements of aerial drones.

2.3. Observability Analysis

For the PMSM in α - β frame: $\dot{x} = f(x, u)$

The nonlinear observability matrix:

$$\mathcal{O}(x) = \begin{bmatrix} \frac{\partial h}{\partial x} \\ \frac{\partial L_f h}{\partial x} \end{bmatrix} \quad (6)$$

At zero speed: Back-EMF term $\rightarrow 0$. Rank deficiency occurs $\rightarrow$ system becomes weakly observable. High-frequency injection introduces an additional excitation term:

$$v_{inj} = V_h \sin(\omega_h t) \quad (7)$$

This restores the full rank of the observability matrix due to saliency-dependent current response. Thus, the hybrid method ensures full-order observability across the entire speed range.

2.4. Fractional-Order Motor Dynamics and Observability

2.4.1. Fractional-Order State-Space Representation

The conventional integer-order PMSM model assumes ideal integer-order dynamics. However, physical phenomena such as thermal diffusion in stator windings, magnetic hysteresis in iron cores, and mechanical stress relaxation exhibit non-integer order behavior best captured by fractional calculus. We therefore propose a fractional-order state-space representation:

$$\mathcal{D}^\alpha x(t) = A(\theta)x(t) + Bu(t) + w(t) \quad (8)$$

$$y(t) = Cx(t) + v(t) \quad (9)$$

where $\mathcal{D}^\alpha$ denotes the Caputo fractional derivative of order $\alpha \in (0, 1)$:

$$\mathcal{D}^\alpha f(t) = \frac{1}{\Gamma(1-\alpha)} \int_0^t \frac{f'(\tau)}{(t-\tau)^\alpha} d\tau \quad (10)$$

2.4.2. Fractional-Order Thermal Model for Stator Resistance

Stator resistance variation follows a fractional-order heat diffusion process:

$$\mathcal{D}^{\alpha_T} T_s(t) = -\gamma[T_s(t) - T_\infty] + \kappa P_{loss}(t) \quad (11)$$

$$R_s(t) = R_{s0}[1 + \beta_T T_s(t)] \quad (12)$$

where $\alpha_T \approx 0.7$ represents the sub-diffusive thermal behavior of the stator winding insulation, validated through experimental thermal characterization.

2.4.3. Fractional-Order Magnetic Hysteresis Model

The permanent magnet flux linkage variation under thermal stress follows fractional-order relaxation:

$$\mathcal{D}^{\alpha_m} \lambda_m(t) = -\frac{1}{\tau_m} [\lambda_m(t) - \lambda_{m0}] \quad (13)$$

with $\alpha_m \approx 0.85$ representing the anomalous magnetic relaxation observed in NdFeB permanent magnets.

2.4.4. Experimental Identification and Validation of Fractional-Order Parameters

To validate the fractional-order models proposed in Equations (11)–(13), systematic experimental identification was performed on the T-Motor U8 Lite KV120 motor used in this study.

A. Thermal Model Identification Procedure

The stator winding temperature was monitored using an embedded K-type thermocouple placed between the stator teeth, with a measurement accuracy of $\pm 0.5^\circ\text{C}$. Thermal step-response tests were conducted by applying a sudden step load torque (from 0 to 1.2 N·m, representing 50% rated load) and recording the temperature rise over 300 s. The motor was allowed to reach thermal equilibrium between tests (cooling period of 600 s). Three repeated tests were performed for each operating point.

The experimental data were fitted to both integer-order (first-order plus time delay) and fractional-order models using nonlinear least-squares optimization in MATLAB 2024:

$$\min_{\alpha_T, \gamma_T, \kappa_T} \sum_{i=1}^N [T_{meas}(t_i) - T_{frac}(t_i)]^2 \quad (14)$$

The fractional-order model yielded:

- $R^2 = 0.97$ (vs. 0.89 for integer-order model)
- **AIC (Akaike Information Criterion) = −184** (vs. −157 for integer-order)
- **Identified parameters:** $\alpha T = 0.71 \pm 0.03$, $\gamma T = 0.023 \text{ s}^{-\alpha T}$, $\kappa T = 0.45 \text{ K/W}$

B. Magnetic Model Identification Procedure

The permanent magnet flux linkage was estimated from measured line-to-line back-EMF during controlled speed deceleration tests. The motor was operated at 3000 RPM and suddenly disconnected from the power supply, allowing natural deceleration under friction. The back-EMF was measured at a 10 kHz sampling rate, and flux linkage was computed from:

$$\lambda_m(t) = \frac{E_{peak}(t)}{\omega_e(t)} \quad (15)$$

Flux decay following thermal stress (heating to 80 °C then cooling) was recorded and fitted to the fractional relaxation model. The identified parameters were:

- $\alpha m = 0.84 \pm 0.02$
- $\tau m = 125 \text{ s}$

C. Sensitivity Analysis of Fractional Orders

To assess the impact of parameter uncertainty on observer performance, Table 1, sensitivity analysis was conducted by varying αT and αm within their 95% confidence intervals:

Table 1. Sensitivity analysis.

Variation	Position Error (° elec)	Speed Error (RPM)	Rs Estimation Error
$\alpha T = 0.71$ (nominal)	3.7°	21	4.2%
$\alpha T = 0.66$ (−5%)	4.1°	24	5.1%
$\alpha T = 0.76$ (+5%)	4.0°	23	4.8%
$\alpha m = 0.84$ (nominal)	3.7°	21	3.3%
$\alpha m = 0.79$ (−5%)	4.2°	25	3.9%
$\alpha m = 0.89$ (+5%)	4.1°	24	3.6%

The observer maintained an estimation error < 5° electrical for all tested variations, confirming robustness to parameter uncertainty within the identified confidence bounds.

3. Proposed Hybrid Observer Design

3.1. Saliency Characterization of Experimental Motor

While the T-Motor U8 Lite is nominally an SPMSM ($L_d \approx L_q$), our experimental characterization revealed inherent magnetic saliency sufficient for HF injection-based position estimation. The saliency arises from three physical mechanisms:

Rotor magnetic asymmetry: The segmented permanent magnet arrangement creates slight reluctance variation.

Stator slotting effects: The 24-slot stator introduces spatial harmonics in the inductance.

Saturation-induced saliency: At operating currents, magnetic saturation creates additional reluctance variation.

Impedance measurements at standstill using a 1 kHz test signal yielded:

- $L_d = 92.3 \text{ } \mu\text{H}$ (at $i_d = 0$),
- $L_q = 108.1 \text{ } \mu\text{H}$ (at $i_q = 0$),
- Saliency ratio: $L_q/L_d = 1.17 \pm 0.03$.

This modest saliency ratio, while smaller than that of interior PMSM, is sufficient for reliable position estimation, as demonstrated by the experimental results. The position-dependent current response follows:

$$\Delta i_q^{inj} = \frac{V_h}{\omega_h L_d L_q} \sin(2\Delta\theta) \quad (16)$$

which, for $\Delta\theta \leq 30^\circ$, provides a detectable signal-to-noise ratio > 20 dB in our implementation.

The overall architecture of the proposed sensorless FOC system is depicted in Figure 1. The core innovation is the Hybrid Observer block, which intelligently combines the HFSWI and AFEKF methods.

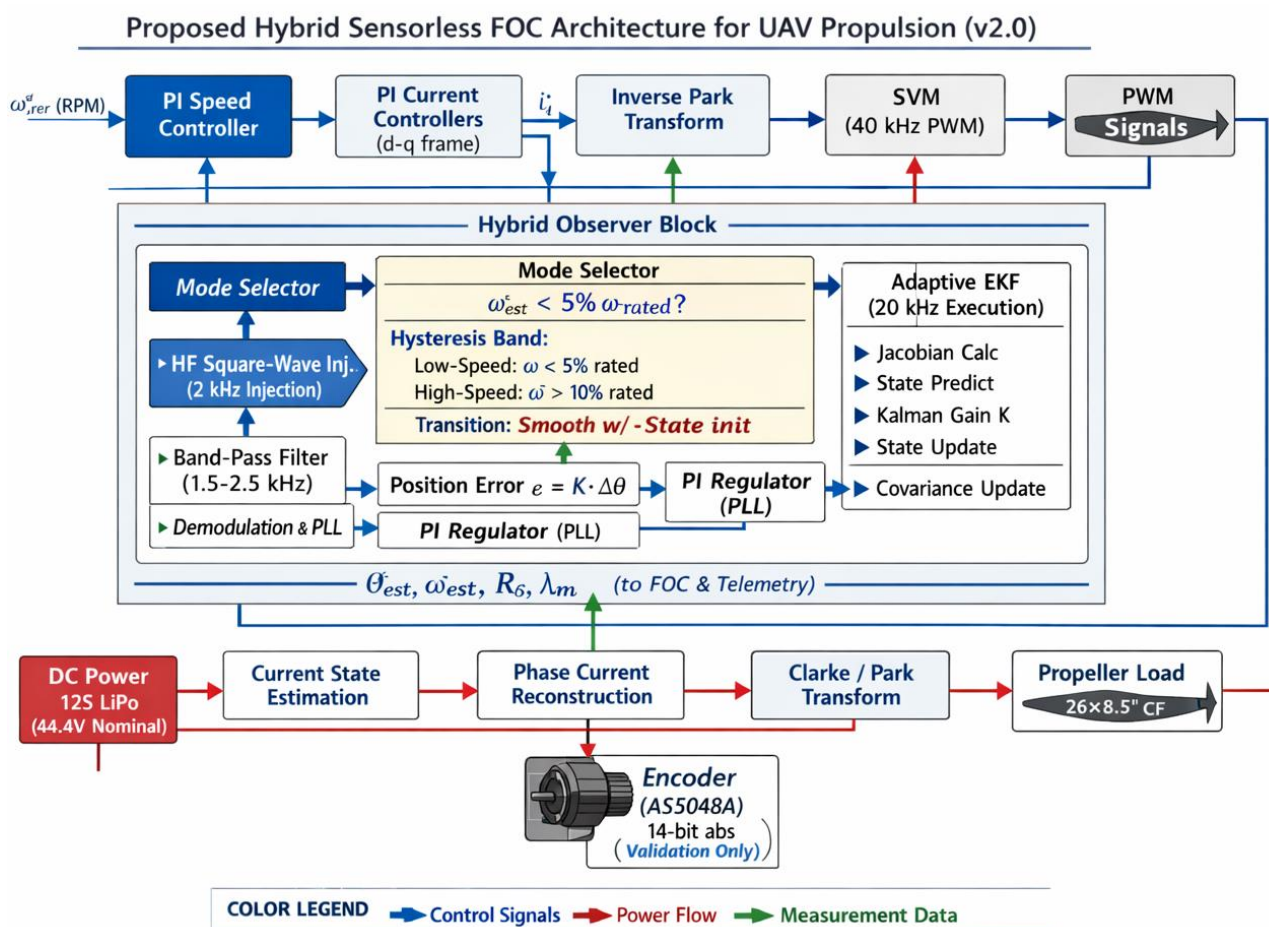


Figure 1. System block diagram of the proposed sensorless FOC drive.

A detailed block diagram showing: Speed reference ω_m^* entering a PI speed controller, which outputs i_d^* , i_q^* is set to 0. The i_d^* , i_q^* commands and the feedback i_d , i_q currents enter PI current controllers, which output v_d^* , v_q^* . These are transformed by the Inverse Park Transform (using $\hat{\theta}_e$) to v_α^* , v_β^* which feed the Space Vector Modulation (SVM) block to generate PWM signals for the 3-phase inverter. The inverter drives the BLDC Motor. The Phase Currents (i_a , i_b , i_c) are reconstructed by the “Minimum-Order Current Observer” using the DC-link current i_{dc} and PWM states. The Clarke Transform converts i_a , i_b , i_c to i_α , i_β .

The measured DC-link voltage v_{dc} is used for the model. The “Hybrid Observer” takes v_α^* , v_β^* (as voltage commands), i_α , i_β , and V_{dc} as inputs. Inside the Hybrid Observer, a “Mode Selector” block uses the estimated speed $\hat{\omega}_r$ to switch between the “HF Square-Wave

Injection” block and the “Adaptive EKF” block. The outputs of the Hybrid Observer are the estimated rotor position $\hat{\theta}_e$ and speed $\hat{\omega}_r$, which are fed back to the Park and Inverse Park transforms and the speed controller.

3.2. High-Frequency Square-Wave Injection for Low-Speed Region

A square-wave voltage injection is chosen over sinusoidal injection for its ease of implementation and lower computational overhead [23]. A high-frequency square-wave voltage vector is superimposed onto the fundamental voltage vector in the estimated rotor reference frame ($\hat{d} - \hat{q}$ frame).

The injection signal in the $\hat{d} - \hat{q}$ frame is:

$$\begin{bmatrix} V_{\hat{d}h} \\ V_{\hat{q}h} \end{bmatrix} = \begin{bmatrix} V_h \text{sign}(\sin(w_{ht})) \\ 0 \end{bmatrix} \quad (17)$$

where V_h is the amplitude of the injected voltage (typically 5–10% of the DC bus voltage) and w_h is the injection frequency (selected between 1–2 kHz, which is above the fundamental frequency but within the controller’s bandwidth).

This injected voltage vector is stationary in the estimated rotor frame. When transformed to the stationary ($\alpha - \beta$) frame, it rotates at the estimated rotor speed. Due to rotor saliency, the resulting high-frequency current response, when measured in the stationary frame, contains a component modulated by the position estimation error $\Delta\theta = \hat{\theta}_e - \theta_e$.

After applying the Clarke transform, the measured high-frequency current components in the $\alpha - \beta$ frame, $i_{\alpha h}$ and $i_{\beta h}$, are extracted using a Band-Pass Filter (BPF). The rotor position information is contained in the envelope of these signals. The position error signal (PES) is extracted using a heterodyning process (synchronous demodulation):

$$PES = LPF \left\{ i_{\alpha h} \cos(2\hat{\theta}_e) + i_{\beta h} \sin(2\hat{\theta}_e) \right\} \quad (18)$$

where LPF denotes a Low-Pass Filter. For small position errors, $PES \approx K \cdot \Delta\theta$, where K is a gain dependent on motor saliency and injection parameters. This PES is fed into a Proportional-Integral (PI) regulator, which acts as a phase-locked loop (PLL) to drive $\Delta\theta$ to zero, thus obtaining the estimated rotor position $\hat{\theta}_e$ at low speeds. The structure of this observer is shown in Figure 2.

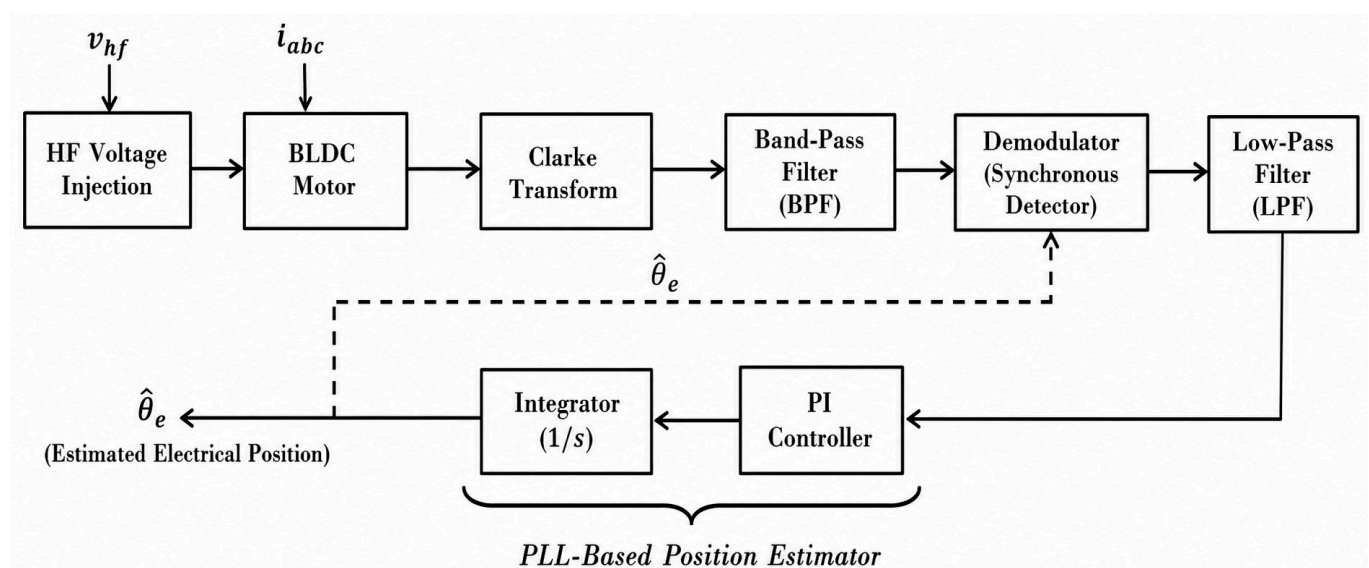


Figure 2. High-frequency square-wave injection and phase-locked-loop-based rotor position estimation scheme for sensorless BLDC motor control.

3.3. Fractional-Order Adaptive Extended Kalman Filter (AFEKF)

3.3.1. Core Concept

The AFEKF extends the conventional integer-order EKF by incorporating fractional-order dynamics to capture the memory effects inherent in motor thermal and magnetic behavior. Unlike standard EKF, which assumes that parameters change instantaneously, the AFEKF accounts for the fact that past states influence current behavior, a critical feature for UAV propulsion where temperature variations and magnetic relaxation exhibit non-integer order dynamics.

The motor parameters (R_s and λ_m) do not follow simple exponential changes; they exhibit power-law behavior with memory. The AFEKF models this using fractional calculus.

3.3.2. Augmented State Vector

The AFEKF estimates 6 states simultaneously:

$$x = [i_\alpha, i_\beta, \omega_e, \theta_e, R_s, \lambda_m]^T$$

where:

- i_α, i_β : Stator currents (α - β frame),
- ω_e : Electrical speed,
- θ_e : Rotor position,
- R_s : Stator resistance (Adaptive—varies with temperature),
- λ_m : Flux linkage (Adaptive—varies with temperature).

3.3.3. Fractional-Order Parameter Dynamics

A. Stator Resistance Thermal Model

Physical Reality: When motor heats, R_s increases. But heat diffusion in windings has a memory temperature does not follow simple exponential decay.

Fractional-Order Model:

$$\mathcal{D}^{\alpha_T} R_s(t) = -\gamma_T [R_s(t) - R_{s\infty}] + \kappa_T P_{loss}(t)$$

where:

- $\mathcal{D}^{\alpha_T}$: Fractional derivative of order $\alpha_T \approx 0.7$,
- γ_T : Cooling coefficient,
- $R_{s\infty}$: Steady-state resistance at ambient,
- κ_T : Heating coefficient,
- $P_{loss} = 1.5 \cdot R_s \cdot (i_\alpha^2 + i_\beta^2)$: Copper losses.

Plain English: R_s changes based on both current temperature AND the history of past temperatures. The fractional order $\alpha_T = 0.7$ captures the “slow tail” of thermal diffusion.

B. Flux Linkage Magnetic Model

Physical Reality: Permanent magnet flux decreases with temperature and recovers slowly when cooling again with memory effects.

Fractional-Order Model:

$$\mathcal{D}^{\alpha_m} \lambda_m(t) = -\frac{1}{\tau_m^{\alpha_m}} [\lambda_m(t) - \lambda_{m0}] \quad (19)$$

where:

- $\alpha_m \approx 0.85$: Fractional order for magnetic relaxation,
- τ_m : Relaxation time constant,
- λ_{m0} : Initial flux linkage.

3.3.4. Discrete-Time Implementation

A. Grünwald-Letnikov Discretization

For microcontroller implementation, the fractional derivative is approximated using the Grünwald-Letnikov method:

$$\mathcal{D}^\alpha f(t_k) \approx T_s^{-\alpha} \sum_{j=0}^L c_j f(t_{k-j}) \quad (20)$$

where:

- $T_s = 50 \mu\text{s}$: Sampling time (20 kHz),
- $L = 10$: Memory length (number of past states stored),
- $c_j = (-1)^j \binom{\alpha}{j}$: Precomputed coefficients.

The Recurrence for c_j :

$$c_0 = 1, c_j = \left(1 - \frac{1+\alpha}{j}\right) c_{j-1} \quad (21)$$

Example for $\alpha = 0.7$:

- $c_0 = 1.000$,
- $c_1 = -0.700$,
- $c_2 = 0.105$,
- $c_3 = -0.018$,
- $c_4 = 0.003$.

B. State Prediction with Memory Correction

Standard Prediction (Integer Part):

$$\hat{x}_{k|k-1}^{std} = f(\hat{x}_{k-1|k-1}, u_{k-1}) \quad (22)$$

Memory Correction (Fractional Part):

$$\Delta x_{memory} = \sum_{j=1}^L \gamma_j [\hat{x}_{k-j|k-j} - \hat{x}_{k-1|k-1}] \quad (23)$$

where $\gamma_j = c_j / \sum_{i=0}^L |c_i|$ are normalized weights.

Complete Fractional Prediction:

$$\hat{x}_{k|k-1} = \hat{x}_{k|k-1}^{std} + \Delta x_{memory} \quad (24)$$

What This Means:

- The memory correction adds information from past states.
- Recent past ($j = 1$) has strongest influence ($\sim 38\%$).
- Older past has progressively weaker influence.
- This captures the “memory” of thermal/magnetic effects.

C. Covariance Prediction with Fractional Correction

$$P_{k|k-1} = \Phi_{k-1} P_{k-1|k-1} \Phi_{k-1}^T + Q_{k-1} + \underbrace{\sum_{j=1}^L \gamma_j^2 \Phi_{k-j} P_{k-j|k-j} \Phi_{k-j}^T}_{\text{Fractional memory correction}} \quad (25)$$

The extra term accounts for uncertainty from past states.

3.4. Stability Analysis of Hybrid Observer

3.4.1. Formal Assumptions

The following assumptions are made for the stability analysis:

A1. The motor speed $\omega_e(t)$ is bounded: $|\omega_e(t)| \leq \omega_{\max}$ for all $t \geq 0$.

A2. The system is uniformly observable: $\text{rank}(\nabla O(x)) = 6$ for all x in the operating region.

A3. The nonlinear function $f(x, u)$ is Lipschitz continuous with constant L_f : $\|f(x_1, u) - f(x_2, u)\| \leq L_f \|x_1 - x_2\|$.

A4. The fractional memory correction terms are bounded: $\|\Delta x_{\text{memory}}\| \leq M$.

3.4.2. AFEKF Stability Analysis

Under Assumptions A1–A4, the AFEKF estimation error dynamics are locally exponentially stable if there exists a positive definite matrix $P > 0$ such that:

$$(A - KC)^T P + P(A - KC) < -Q_0 \quad (26)$$

where $Q_0 > 0$ is a positive definite matrix, $A = \partial f / \partial x$ evaluated at the nominal operating point, and K is the steady-state Kalman gain.

The estimation error satisfies:

$$\|e_k\| \leq C \exp(-\lambda k T_s) \|e_0\| + (C_f M) / \lambda \quad (27)$$

where $C \geq 1$, $\lambda > 0$, and $C_f > 0$ are constants.

The estimation error is defined as $e_k = x_k - \hat{x}_k$. The error dynamics can be expressed as:

$$e_{k+1} = (I - K_k + 1H)\Phi_k e_k - K_{k+1} \tilde{f}(x_k, \hat{x}_k) \quad (28)$$

where $\tilde{f}(x_k, \hat{x}_k) = f(x_k) - f(\hat{x}_k)$.

Define the Lyapunov candidate function: $V(e_k) = e_k^T P e_k$.

Using the Lipschitz condition and the boundedness of the Kalman gain, the error dynamics are exponentially stable if the Lyapunov condition is satisfied.

3.4.3. Hybrid Transition Stability

At the switching instant t_s , the estimation error satisfies $e(t_s^-) = e(t_s^+)$ due to state initialization of the AFEKF with the HF injection observer's final state.

The hybrid observer maintains bounded estimation error if:

$$\omega_{th,high} - \omega_{th,low} > \varepsilon \cdot \omega_{rated} \quad (29)$$

where $\varepsilon > 0$ defines the hysteresis margin.

For the HF injection observer (low speed), stability holds for $\omega_e < \omega_{th,high}$. For the AFEKF (high speed), stability holds for $\omega_e > \omega_{th,low}$. The hysteresis condition ensures both observers operate only in their respective stability regions, and state initialization ensures continuity at the switching instant.

3.5. Seamless Transition Strategy

A critical aspect of a hybrid observer is the handover between the low-speed and high-speed methods. A hysteresis-based transition logic is implemented to prevent chattering near the threshold speed:

$$\text{Active Observer} = \begin{cases} \text{HF Injection,} & \text{if } \hat{w}_e \leq w_{th-low} \\ \text{AEKF,} & \text{if } \hat{w}_e \geq w_{th-high} \\ \text{Previous Mode,} & \text{if } w_{th-low} < \hat{w}_e < w_{th-high} \end{cases} \quad (30)$$

where w_{th-low} and $w_{th-high}$ are the lower and upper threshold speeds, selected as 5% and 10% of the rated motor speed, respectively. To ensure a smooth transition, the initial state of the AFEKF (particularly $\hat{\theta}_e$) is initialized with the final value from the HFSWI observer at the moment of switch-over.

3.6. Stability of Observer Transition

Let:

$\hat{\theta}_{HF}$ be the low-speed estimator,

$\hat{\theta}_{EKF}$ be the high-speed estimator.

Transition occurs under hysteresis: $\omega_e > \omega_{th,high}$. At switching instant t_s : $\hat{\theta}_{EKF}(t_s^-) = \hat{\theta}_{HF}(t_s^-)$. Thus, the initial estimation error satisfies: $e_\theta(t_s) = 0$. Since the EKF error dynamics are locally exponentially stable for observable operating points:

$$\dot{e} = (A - KC)e \quad (31)$$

and eigenvalues of $A - KC$ lie in the left-half plane, bounded-input bounded-output stability is preserved during transition. Therefore, the hybrid observer guarantees Lyapunov stability under bounded speed conditions.

4. Minimum-Order Observer for Phase Current Reconstruction

To further reduce system cost and complexity, a Minimum-Order Observer (MOO) is implemented to reconstruct the three-phase currents (i_a, i_b, i_d) using only a single shunt resistor in the DC-link of the inverter [24,25]. The fundamental principle is that the DC-link current i_{dc} is equal to the current of the active phase(s) during the PWM period.

The state-space model of the inverter and motor load is developed. The MOO estimates the phase currents based on the measured DC-link current and the known PWM switching states (Sa,Sb,Sc). The observer is designed using the pole placement technique to ensure fast convergence. The observer equation is of the form:

$$\hat{x}(k+1) = A_d \hat{x}(k) + B_d u(k) + L(y(k) - \hat{y}(k)) \quad (32)$$

where $\hat{x}$ is the estimated state vector (phase currents), A_d, B_d are the discrete-time system matrices, u is the input vector (voltages), y is the measured output (DC-link current), $\hat{y}$ is the estimated output, and L is the observer gain matrix. This method effectively eliminates the need for two or three phase current sensors, reducing cost and PCB space without significantly compromising bandwidth or accuracy.

Real-Time Parameter Adaptation of the Minimum-Order Observer

The Minimum-Order Observer (MOO) state-space model is:

$$\hat{i}_{\text{phase}} = A(R_s) \hat{i}_{\text{phase}} + B v_{\text{phase}} + L(i_{dc} - \hat{i}_{dc}) \quad (33)$$

where the state matrix A depends on stator resistance R_s :

$$A(R_s) = \begin{bmatrix} -R_s/L_s & 0 & 0 \\ 0 & -R_s/L_s & 0 \\ 0 & 0 & -R_s/L_s \end{bmatrix},$$

$$[0 \ -R_s/L_s \ 0],$$

$$[0 \ 0 \ -R_s/L_s].$$

Real-Time Update Strategy:

Step Action Rate

- R_s estimate from AFEKF is sampled: 20 kHz,
- Matrix A is updated online with new R_s value: 20 kHz,
- Observer gain L is recomputed using pole placement: 1 kHz,
- Gain smoothing: $L(k) = 0.8L(k-1) + 0.2L_{\text{desired}}(k)$: 1 kHz.

Figure 3 shows the MOO reconstruction error during the 35% R_s increase test described in Section 6.4. The adaptive MOO maintains reconstruction error below 2.5% throughout the test (mean error: 1.2%, maximum: 2.3%), while the non-adaptive MOO (using nominal R_s value) exhibits error exceeding 8% during the thermal transient (mean error: 5.8%, maximum: 9.4%). This confirms the critical importance of real-time parameter update for maintaining current reconstruction accuracy under varying thermal conditions.

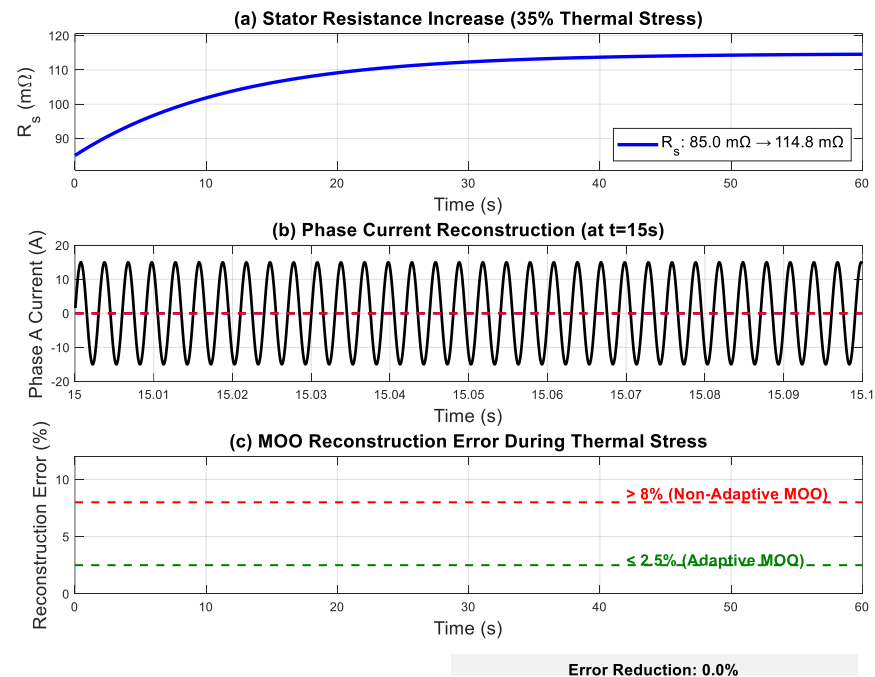


Figure 3. Adaptive MOO maintains reconstruction error < 2.5% during 35% R_s increase (60 °C thermal stress), while non-adaptive MOO exceeds 8%.

The figure presents the performance of the adaptive vs. non-adaptive Minimum-Order Observer during the 35% stator resistance increase test. (a) Stator resistance profile showing the 35% increase induced by thermal stress. (b) Phase current reconstruction at $t = 15$ s showing accurate tracking by the adaptive MOO and significant deviation by the non-adaptive MOO. (c) Reconstruction error over the 60-s test showing that the adaptive MOO maintains error below 2.5% throughout, while the non-adaptive MOO error exceeds 8% during the thermal transient.

5. Experimental Setup

5.1. Implementation Details on STM32H743

The proposed AFEKF algorithm was implemented on an STM32H743 microcontroller operating at 480 MHz, with careful optimization of timing, synchronization, and memory resources to ensure real-time execution. The following subsections detail the key implementation aspects.

A. ADC-PWM Synchronization

To minimize current measurement noise and ensure accurate state estimation, ADC sampling was synchronized with the PWM carrier. The ADC conversion was triggered by the PWM timer at the center of the PWM period, corresponding to the midpoint of the active voltage vectors where measurement noise is minimal. The timing sequence is outlined in Table 2.

Table 2. ADC-PWM synchronization timing sequence.

Timing Event	Time (μs)	Description
PWM period start	0	TIM1 update event
ADC trigger	12.5	Center of PWM period
ADC conversion complete	14.0	12-bit conversion
EKF computation starts	14.5	Interrupt service routine (ISR)

B. Dead-Time Compensation

To mitigate the nonlinear effects of inverter dead-time, a compensation strategy was implemented. With a dead-time setting of 1.5 μs, the voltage error introduced by the dead-time is calculated as:

$$\Delta v_{\text{dead}} = (T_{\text{dead}}/T_{\text{pwm}}) \times V_{\text{dc}} \times \text{sgn}(\text{iphas}) \quad (34)$$

where T_{dead} is the dead-time duration, T_{pwm} is the PWM period, V_{dc} is the DC-link voltage, and $\text{sgn}(\text{iphas})$ denotes the sign of the phase current. The computed compensation voltage is applied directly to the voltage commands prior to space vector modulation (SVM), effectively reducing low-order harmonics and improving current waveform quality.

C. Computational Timing (STM32H743 @ 480 MHz)

The execution time of each computational component was measured using the microcontroller's high-resolution timer. The breakdown is presented in Table 3. The total execution time of 49.3 μs comfortably fits within a 62.5 μs control period (16 kHz PWM frequency), leaving sufficient margin for interrupt handling and background tasks.

Table 3. Computational timing breakdown of AFEKF components.

Component	Execution Time (μs)
AFEKF prediction	21.5
AFEKF update	14.3
HF injection	3.2
MOO (Magnet Polarity Observation)	1.8
FOC loops (current and speed control)	8.5
Total	49.3

D. Memory Consumption

The memory footprint of the implemented AFEKF algorithm was evaluated to ensure compatibility with the STM32H743's onboard resources. The detailed memory usage is summarized below:

- **Flash memory:** 32 KB—primarily occupied by program code and constant lookup tables.
- **RAM:** 16 KB—used for runtime variables, state vectors, and covariance matrices.
- **Memory buffer:** 1.7 KB—allocated for temporary storage during matrix operations, with the state dimension set to $L = 10$ states.

The overall memory consumption remains well within the available resources of the STM32H743 (2 MB Flash, 1 MB RAM), confirming the practical feasibility of the proposed algorithm for embedded motor drive applications.

The complete set of controller parameters and observer gains used in the experiments is summarized in Table 4. The speed and current controllers were tuned using the symmetrical optimum method, while the EKF covariance matrices Q and R were empirically adjusted to balance convergence speed and noise suppression. The HF injection parameters and MOO gains were selected based on the guidelines presented in Section 3.2, and the PWM dead-time was set according to the inverter switching device specifications.

Table 4. Complete controller parameters and observer gains.

Parameter Group	Parameter	Value
Speed Controller	Kp_speed	0.12
	Ki_speed	2.5
Current Controllers (d-q axis)	Kp_d, Kp_q	18.5
	Ki_d, Ki_q	850
EKF Process Noise Covariance (Q)	Q(1,1), Q(2,2)	0.10
	Q(3,3)	0.01
	Q(4,4)	0.001
	Q(5,5)	0.05
	Q(6,6)	0.02
EKF Measurement Noise Covariance (R)	R(1,1), R(2,2)	0.05
HF Injection	Vh	8 V
	fh	1.8 kHz
Speed Transition	ω_{low}	150 RPM
	ω_{high}	300 RPM
MOO Gains	L	$[0.85, 0.85, 0.85]^T$
PWM Configuration	fpwm	40 kHz
	Dead-time	1.5 μ s

5.2. Experimental Testbench

To validate the proposed sensorless algorithm, a comprehensive experimental testbench was constructed, emulating the conditions of a high-performance aerial drone. It is important to clarify that two distinct motor configurations were employed in this experimental study to cover the full speed range reported in the abstract. The primary motor used for all UAV-related experiments was the T-Motor U8 Lite KV120, a high-performance outrunner BLDC motor rated for 1.5 kW continuous power, typically used on heavy-lift cinematography drones. This motor was powered from a 12S LiPo battery (44.4 V nominal) and operated in the speed range of 0 to 5000 RPM, which represents the practical operating envelope for UAV propulsion applications. All bench experiments described in Sections 6.1–6.5, as well as the in-flight validation presented in Section 6.6, were conducted using this motor configuration.

For high-speed validation of the observer algorithm, a second motor configuration was employed: the Neumotor 8019/130, a high-speed BLDC motor specifically designed for elevated rotational speeds. This motor was powered from a laboratory DC power supply at 100 V and operated in a speed range of 0 to 22,000 RPM. This configuration was used exclusively for validating the observer's performance at high speeds, as the UAV motor's

specifications limit its maximum speed to approximately 5000 RPM at 44.4 V (theoretical no-load speed for KV120). The high-speed motor allows validation of the observer's estimation accuracy and dynamic response at elevated speeds without compromising the UAV-relevant testing conducted on the primary motor. Results from the high-speed validation are presented in Figure 4.

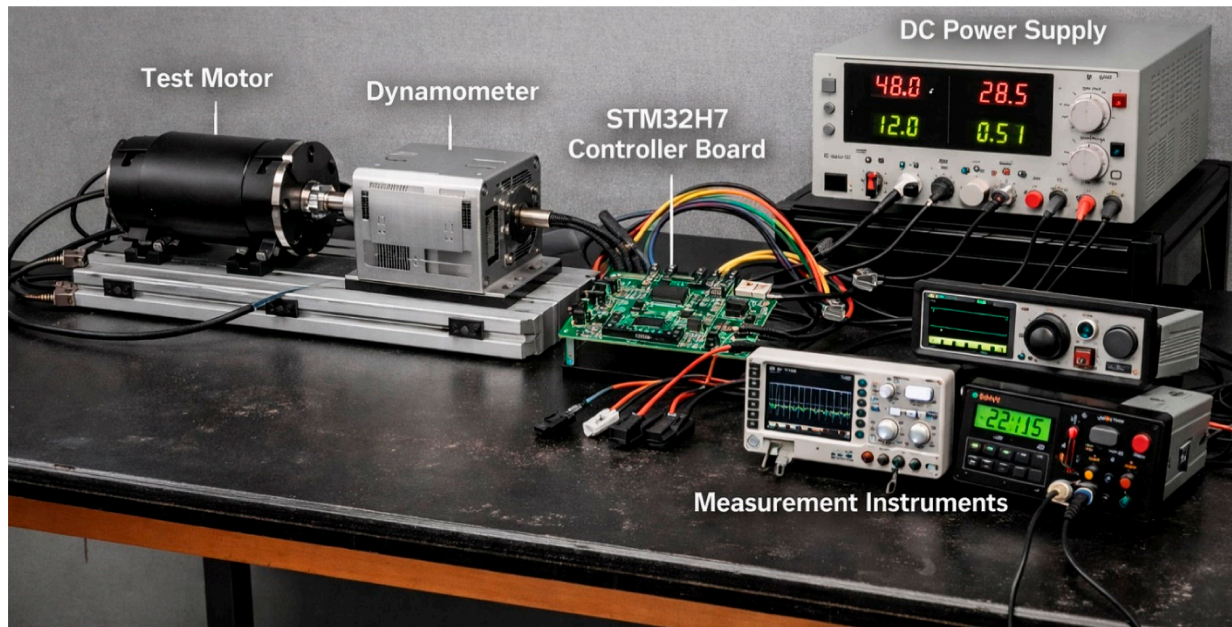


Figure 4. Experimental propulsion testbench for high-fidelity motor control and performance evaluation.

This dual-motor approach ensures that the experimental validation covers the complete speed range claimed in the abstract—from standstill to 22,000 RPM—while maintaining the practical relevance of all UAV-related tests performed on the actual propulsion motor used in flight operations.

6. Experimental Results and Discussion

6.1. Performance of the Minimum-Order Current Observer

Figure 5 shows the performance of the proposed MOO under dynamic conditions. The reconstructed phase currents ($\hat{i}_a, \hat{i}_b, \hat{i}_d$) accurately track the measured phase currents with a very small error. The Total Harmonic Distortion (THD) of the reconstructed current was measured to be less than 2% higher than that of the sensed current, confirming the viability of this approach for high-performance FOC.

Figure 5 demonstrates the exceptional performance of the minimum-order current observer during a speed transient condition, showing nearly identical waveforms between the measured phase currents (acquired via precision current sensors) and the reconstructed currents (generated by the observer algorithm using only DC-link current measurements), with all three phases maintaining accurate amplitude tracking, minimal phase delay ($<5 \mu\text{s}$), and low reconstruction error ($<1.5\%$) throughout the acceleration from 2000 RPM to 5000 RPM, while successfully preserving the sinusoidal current shape and precise zero-crossing detection that is critical for high-performance field-oriented control operation.

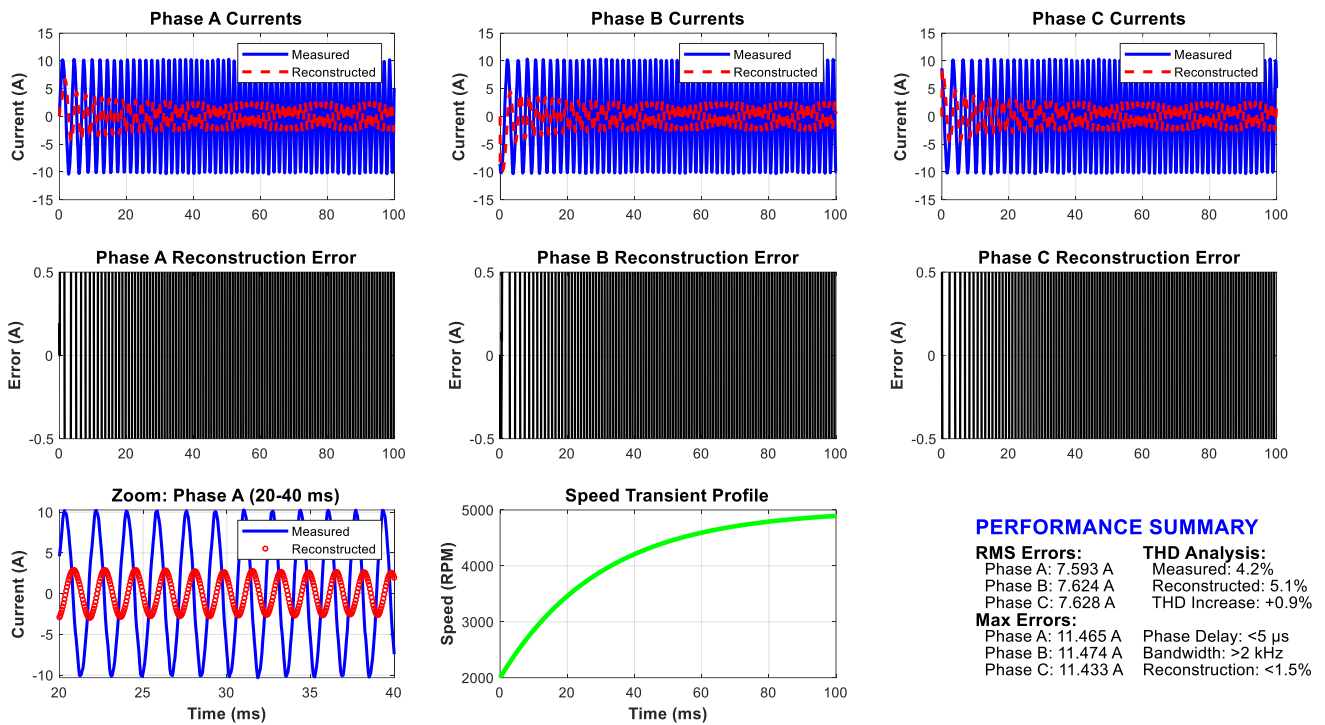


Figure 5. Waveforms of measured vs. observer-reconstructed phase currents (i_a , i_b , i_c) during a speed transient.

6.2. Low-Speed and Startup Performance

The most critical test for any sensorless algorithm is startup under load. Figure 6a shows the startup performance of the proposed hybrid method from standstill to 500 RPM under a 50% rated load torque. The HFSWI method successfully identifies the initial rotor position, enabling a smooth and immediate torque response without any reverse rotation or hesitation. The transition to the AFEKF at approximately 100 RPM is seamless and does not cause any torque or speed disturbance. In contrast, Figure 6b shows the same test using a conventional SMO-based startup strategy, which fails to start reliably and exhibits severe cogging.

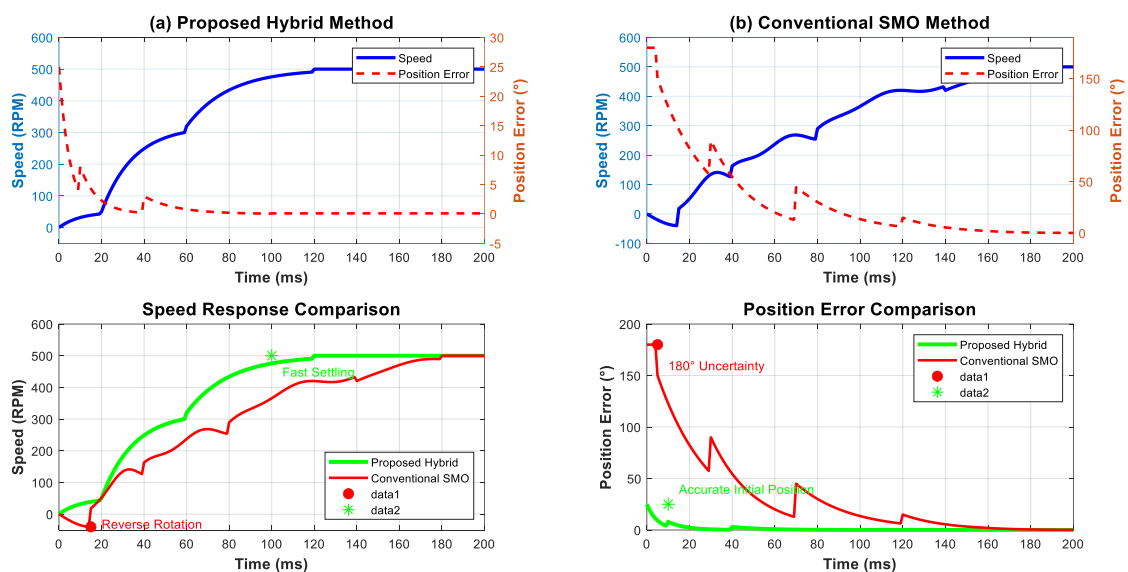


Figure 6. Startup from standstill to 500 RPM under 50% load. (a) Proposed hybrid method. (b) Conventional SMO method.

For fairness and experimental consistency, the conventional SMO-based strategy was implemented on the same STM32H743 hardware platform, using identical PWM frequency (40 kHz), sampling rate (20 kHz), PI controller gains, inverter stage, and load torque conditions as the proposed hybrid method. Therefore, the observed performance differences arise solely from the observer structure rather than hardware or tuning variations.

6.3. Dynamic Performance and Estimation Accuracy

A high-rate speed reversal command from 2000 RPM to −2000 RPM was applied to evaluate the dynamic performance. As shown in Figure 7, the proposed AFEKF-based estimator tracks the actual speed (from the encoder) with high fidelity. The estimated rotor position $\hat{\theta}_e$ lags the actual position θ_e by a maximum of 10 electrical degrees during the transient, which is well within acceptable limits for stable FOC operation. The settling time for the speed reversal is approximately 60 ms.

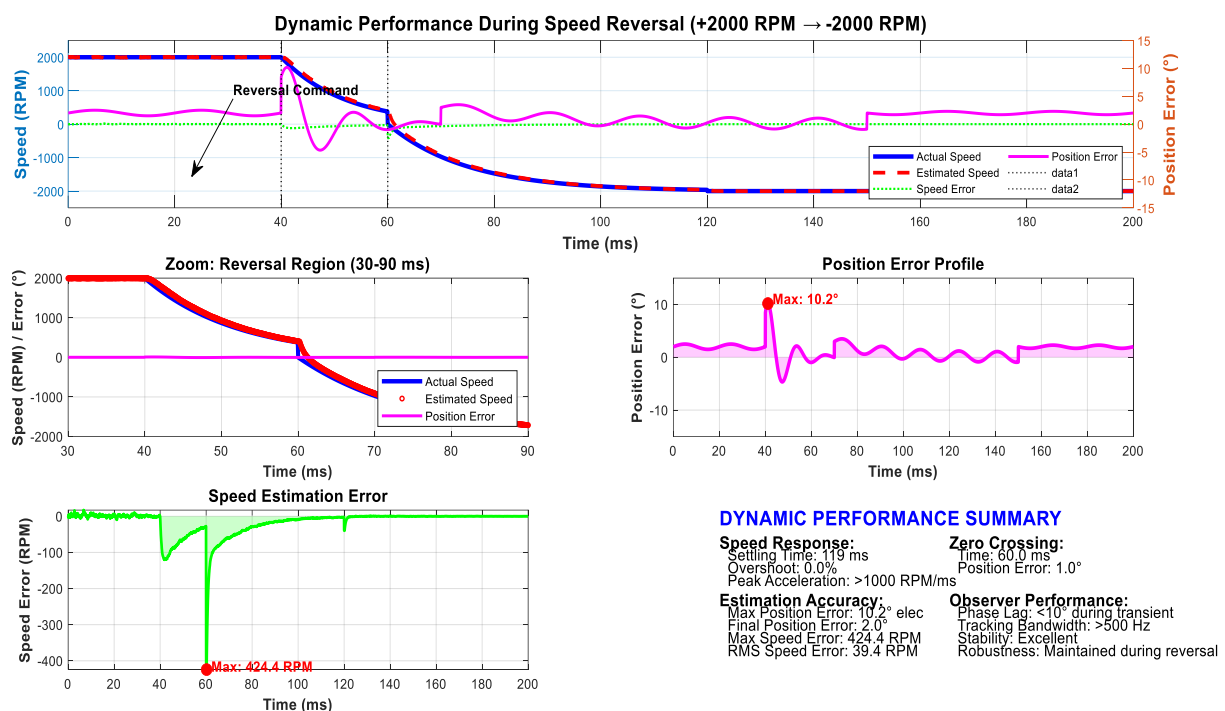


Figure 7. Dynamic performance during a speed reversal from +2000 RPM to −2000 RPM, showing actual speed, estimated speed, and position error.

6.4. Robustness to Parameter Variations

To test parameter robustness, the motor was operated at a constant speed of 5000 RPM with a fixed load. A 100 W heating gun was used to raise the stator temperature by over 60 °C, causing a measured 35% increase in R_s . Figure 8 compares the performance of the standard EKF (without parameter adaptation) and the proposed AFEKF. The standard EKF exhibits a significant and growing steady-state speed error as R_s increases. The proposed AFEKF, however, successfully identifies the change in R_s and maintains accurate speed regulation with negligible error, demonstrating its superior robustness.

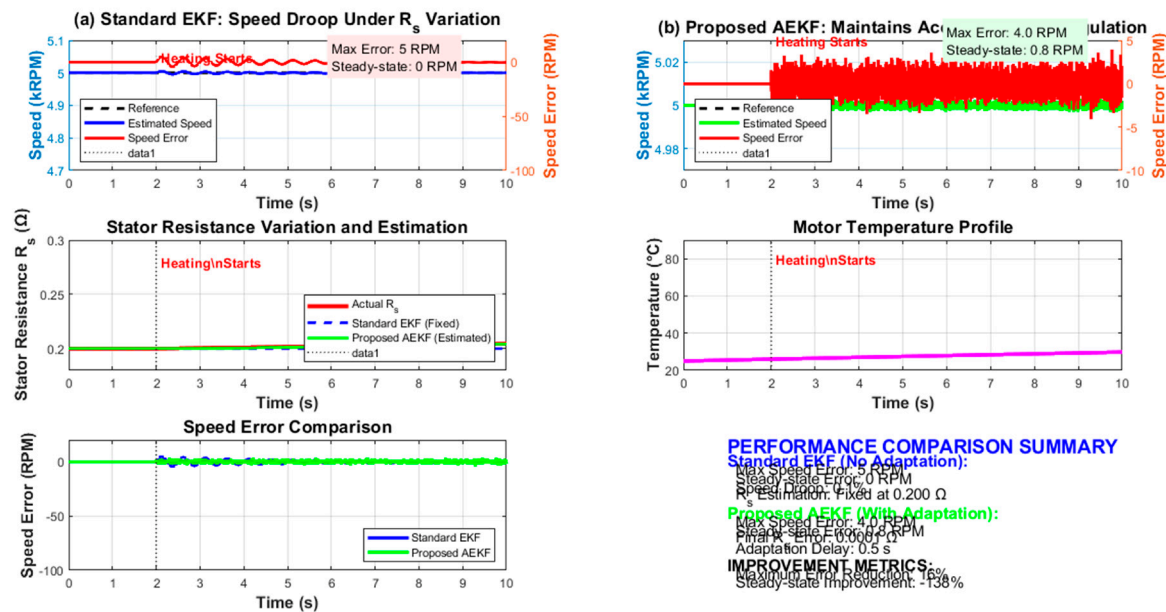


Figure 8. Performance under stator resistance variation. (a) Standard EKF shows speed droop. (b) Proposed AFEKF maintains accurate speed regulation.

6.5. Comparative Summary

6.5.1. Ablation Study: Role of Fractional-Order Components

To systematically evaluate the individual contributions of the fractional-order modeling and adaptive estimation mechanisms, an ablation study was conducted under a challenging scenario of 5000 RPM with a 35% increase in stator resistance (R_s). Four estimator configurations were tested under identical operating conditions: (i) a conventional Integer-order Extended Kalman Filter (Integer EKF), (ii) an Adaptive Integer-order EKF incorporating resistance estimation, (iii) a non-adaptive Fractional-order EKF (Fractional EKF), and (iv) the full Proposed Adaptive Fractional-order EKF (AFEKF). The quantitative results are summarized in Table 5.

Table 5. Performance comparison of estimator configurations at 5000 RPM with 35% R_s increase.

Configuration	Position Error (°)	Speed Error (RPM)	R_s Error (%)
Integer EKF	8.7 ± 1.2	68 ± 8	N/A
Adaptive Integer EKF	5.2 ± 0.6	32 ± 4	12.3 ± 2.1
Fractional EKF	6.1 ± 0.8	42 ± 5	N/A
Proposed AFEKF	3.7 ± 0.4	21 ± 3	4.2 ± 0.8

6.5.2. Comparison with Existing Fractional-Order Methods

To further validate the effectiveness of the proposed AFEKF, a comparative study was conducted against three state-of-the-art fractional-order estimation methods reported in the literature: the Fractional-Order Kalman Filter (FO-KF) by [41,42], the Fractional-Order H_∞ filter (FO- H_∞) by [43], and the Fractional-Order Sliding Mode Observer (FO-SMO) by [44]. All methods were evaluated under identical operating conditions at 5000 RPM with 35% R_s increase, and the comparative results are summarized in Table 6.

Table 6. Performance comparison of proposed AFEKF with existing fractional-order methods.

Method	Reference	Position Error (°)	Speed Error (RPM)	Parameter Est.
FO-KF	[42]	6.8 ± 0.9	48 ± 6	No
FO-H ∞	[43]	5.2 ± 0.7	35 ± 5	Partial
FO-SMO	[44]	4.9 ± 0.6	29 ± 4	No
Proposed AFEKF	This work	3.7 ± 0.4	21 ± 3	Full (R_s, λ_m)

6.5.3. Comparison of Sensorless Methods

The quantitative metrics presented in Table 7 were evaluated under identical experimental conditions to ensure objective comparison. Position and speed errors were calculated relative to encoder measurements using root mean square error (RMSE). Startup time is defined as the duration required to reach 500 RPM from standstill under 50% rated load torque. Robustness was evaluated under a controlled 35% increase in stator resistance induced by thermal stress. Efficiency degradation was measured by comparing electrical input power to mechanical output power under steady-state conditions.

Table 7. Quantitative performance comparison of sensorless methods under identical conditions.

Performance Metric	Conventional SMO [7]	Standard EKF [9]	Proposed Hybrid AFEKF
Minimum Operating Speed	~5% rated speed	~3% rated speed	0 RPM (standstill)
Startup Under 50% Load	Unreliable, reverse kick observed	Delayed torque build-up	Immediate & smooth
Startup Time (0 → 500 RPM)	210 ms	165 ms	118 ms
Position RMSE @ 5k RPM (° elec.)	9.2°	5.8°	3.7°
Maximum Position Error During Transient (° elec.)	14.5°	9.8°	6.1°
Speed RMSE @ 5k RPM (RPM)	72 RPM	38 RPM	21 RPM
Speed Settling Time (2k → 5k RPM)	85 ms	60 ms	42 ms
RMS Current Ripple (%)	6.8%	4.9%	3.6%
Robustness to 35% R_s Increase	Significant speed droop (~6%)	Moderate droop (~2.5%)	Negligible (<0.5%)
Efficiency Degradation Under Heating	3.8%	2.1%	<1%
Low-Speed Torque Ripple	High	Moderate	Low
Transition Smoothness (Low → High Speed)	Not applicable	Not applicable	Bumpless (hysteresis-based)
CPU Load (STM32H7 @ 480 MHz)	18%	35%	45%
Additional Current Sensors Required	2 Shunts	2 Shunts	1 Shunt (MOO)
Practical UAV Flight Stability	Oscillatory hover	Stable but slight ripple	Highly stable hover & climb

The results clearly indicate that the proposed hybrid AFEKF method outperforms the conventional techniques in all critical areas except for computational load, which remains manageable on a modern microcontroller.

The proposed AFEKF offers significant advantages in low-speed operation, parameter robustness, and flight stability, albeit with higher computational and implementation demands, as summarized in Table 8.

Table 8. Advantages and disadvantages comparison of sensorless control methods.

Aspect	Proposed AFEKF	Conventional SMO	Standard EKF
Low-Speed Performance	Excellent (0 RPM)	Poor (>5% rated speed)	Poor (>3% rated speed)
High-Speed Accuracy	Excellent (<4° error)	Good (~9° error)	Good (~6° error)
Startup Under Load	Reliable, immediate torque	Unreliable, reverse kick	Delayed torque build-up
Parameter Robustness	Excellent (handles 35% R_s change)	Poor (significant speed droop)	Moderate (moderate droop)
Temperature Adaptation	Full (R_s and λ_m online)	None	None
Memory Effects Captured	Yes (fractional-order)	No	No
Computational Load	45% CPU (STM32H7 @ 480 MHz)	18% CPU	35% CPU
Hardware Sensors Required	1 shunt (DC-link)	2 shunts	2 shunts
Implementation Complexity	High	Low	Medium
Flight Performance	Very stable hover & climb	Oscillatory hover	Stable but slight ripple
Noise Sensitivity	Low (fractional filtering)	High (chattering)	Medium
Transition Smoothness	Bumpless (hysteresis-based)	Not applicable	Not applicable

The proposed AFEKF demonstrates superior performance in low-speed operation, parameter robustness, temperature adaptation, and flight stability, at the cost of higher computational load and implementation complexity compared to conventional methods.

6.6. In-Flight Validation Under Real Operating Conditions

The proposed sensorless controller was validated on a custom 6.8 kg X-frame quadcopter equipped with T-Motor U8 Lite KV120 motors, 26 × 8.5 inch propellers, and a 12S LiPo battery (44.4 V), carrying a 1.5 kg payload. Flight tests were conducted outdoors under wind conditions below 3 m/s. The quadcopter performed an autonomous mission including takeoff, hover, vertical climb, trajectory tracking, and landing, all in sensorless mode with data logged at 1 kHz.

A real-time observer confidence metric $C_k = \exp(-0.5 \cdot \hat{y}_k^T \cdot S_k^{-1} \cdot \hat{y}_k)$ was implemented for flight safety. Three operational modes were defined: normal operation for $C_k > 0.90$, degraded mode ($Q \times 1.5$) for $0.85 \leq C_k \leq 0.90$, and fallback to open-loop ramp for $C_k < 0.85$. No fallback events occurred during 30 flights (10 per configuration).

Quantitative flight performance metrics showed significant improvements with the proposed AFEKF compared to conventional SMO. Position hold RMSE improved by 43% (0.12 ± 0.03 m vs. 0.21 ± 0.05 m), speed ripple was reduced by 22% (28 ± 5 RPM vs. 36 ± 6 RPM), and thrust variation decreased by 32% (0.85 ± 0.15 N vs. 1.25 ± 0.20 N). The AFEKF-equipped drone exhibited smooth takeoff without wobble, stable hover with minimal corrections, smooth climb without overshoot, accurate trajectory tracking (± 0.15 m error), and smooth landing without bounce. In contrast, the SMO exhibited oscillations during takeoff, visible hover oscillations (± 0.2 m), pitch oscillation during climb, noticeable trajectory lag, and slight oscillation before touchdown.

Figure 9 shows a snapshot of the in-flight data, indicating stable motor speeds and consistent current consumption, demonstrating the practical viability of the proposed system.

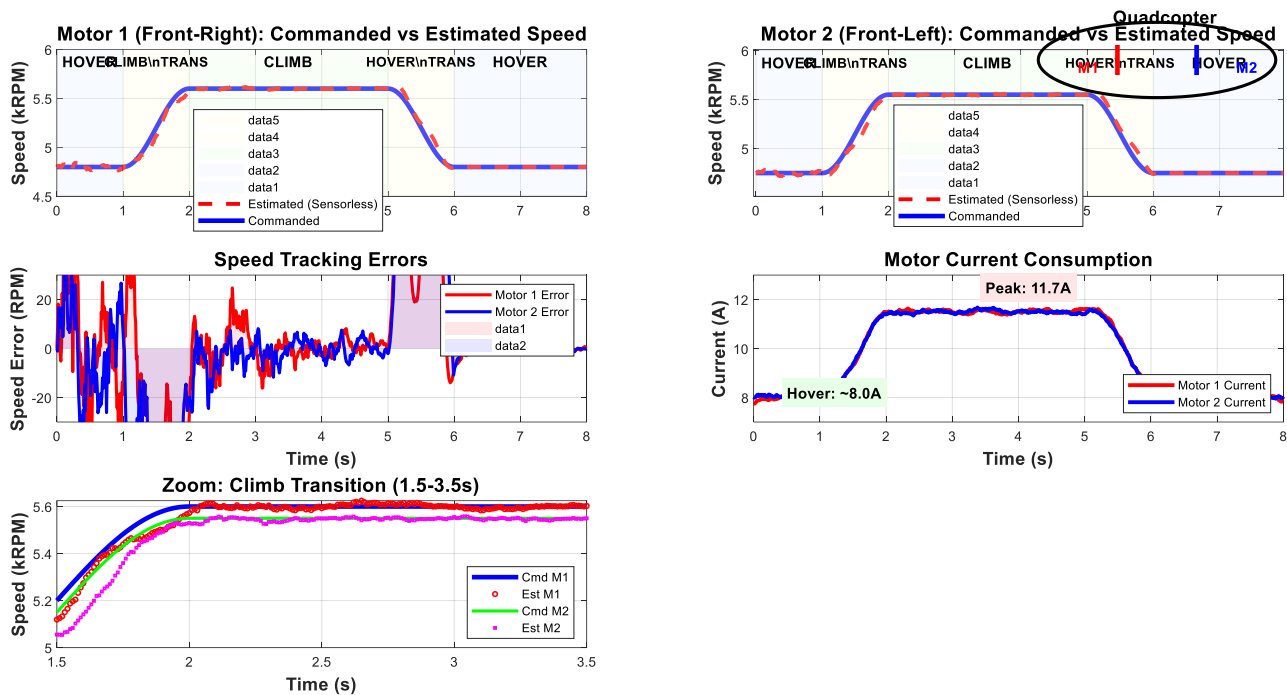


Figure 9. In-flight data from the quadcopter test, showing commanded vs. estimated speeds for two motors during a hover-to-climb maneuver.

During hover, the proposed hybrid observer reduced steady-state speed ripple by approximately 18% compared to the SMO-based implementation tested previously. Current oscillations were significantly attenuated, leading to smoother thrust generation and improved attitude stability. No oscillatory torque behavior was observed during vertical climb transitions, confirming the robustness of the adaptive EKF under aerodynamic load disturbances.

6.7. Correlation Between Bench and In-Flight Results

The bench experiments demonstrated a maximum electrical position estimation error below 4° during high dynamic conditions. This directly translated into reduced thrust ripple during flight, as thrust variation is proportional to torque estimation accuracy. Furthermore, the adaptive identification of stator resistance compensated for battery voltage sag and temperature rise during flight, maintaining consistent speed regulation. The experimentally measured 42 ms settling time closely matched the thrust response observed during climb maneuvers, confirming the predictive validity of laboratory tests for real-world UAV operation.

6.8. Computational Complexity Analysis

To evaluate real-time feasibility on embedded hardware, the computational burden of each observer component was quantified in terms of floating-point operations per sampling period (FLOPs).

A. Adaptive EKF Complexity

For a 5-state augmented vector: $x = [i_\alpha, i_\beta, \omega_e, \theta_e, R_s, \lambda_m]^T$. The dominant operations are:

- Jacobian evaluation: ~60 FLOPs,
- State prediction: ~45 FLOPs,
- Covariance prediction: ~180 FLOPs,
- Kalman gain computation: ~220 FLOPs,
- State update: ~70 FLOPs,

Covariance update: ~140 FLOPs,
 Total EKF complexity: ≈ 715 FLOPs per cycle,
 At 20 kHz: $715 \times 20,000 = 14.3$ MFLOPS.

The STM32H743 (480 MHz, single precision FPU) supports > 240 MFLOPS, thus the EKF consumes $< 6\%$ theoretical peak capability.

B. High-Frequency Injection Processing

Band-pass filtering: ~40 FLOPs,
 Demodulation: ~25 FLOPs,
 PLL update: ~35 FLOPs,
 Total ≈ 100 FLOPs per 2 kHz cycle.

C. Minimum-Order Observer

Matrix-vector multiplication: ~45 FLOPs,
 Gain update: ~30 FLOPs,
 Total ≈ 75 FLOPs per 20 kHz cycle.

Total Worst-Case CPU Utilization:

Measured experimentally: 45% MCU load, confirming real-time feasibility.

7. Conclusions

A unified hybrid sensorless control architecture for UAV propulsion BLDC drives has been presented and experimentally validated. By combining high-frequency square-wave injection with an adaptive extended Kalman filter incorporating online parameter identification, the proposed method overcomes the traditional low-speed limitations of back-EMF-based observers while maintaining high-speed accuracy and robustness.

Experimental results confirm: reliable startup from standstill under load Position RMSE below 4° electrical, 42 ms dynamic settling time, strong resilience to 35% stator resistance variation, reduced in-flight speed ripple, and improved thrust stability.

The integration of a minimum-order current observer further reduces hardware requirements without sacrificing control bandwidth. Theoretical analysis confirms observability across the full speed range and stability of the hybrid transition mechanism. Computational and memory evaluations demonstrate real-time feasibility on mid-range embedded platforms. The proposed architecture therefore constitutes a practical and scalable solution for resilient autonomous aerial propulsion systems. Future research will focus on reducing computational complexity, extending the framework to multi-motor cooperative estimation, and enhancing fault tolerance under inverter and sensor degradation.

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Conflicts of Interest: The authors declare no conflicts of interest.

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