



Excitation-Aware Innovation-Adaptive Dual Extended Kalman Filter for Sensorless Induction-Motor Drives

Vu Quang Luong^{1,*}, Trinh Thi Minh²

¹ Missile Faculty, Air Defence-Air Force Academy, Hanoi, Vietnam

² Basic Sciences Faculty, Air Defence-Air Force Academy, Hanoi, Vietnam

*Corresponding author email: vuquangluong88@gmail.com

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ABSTRACT

Mechanical speed sensors increase cost, wiring, maintenance requirements, and potential failure points in induction-motor drives, while sensorless estimation remains difficult during low-speed operation, load transients, resistance drift, and speed reversal. This study proposes an excitation-aware innovation-adaptive dual extended Kalman filter (EAIA-DEKF) for simultaneous estimation of mechanical speed, load torque, rotor flux, and stator resistance. Its state branch is a six-state extended Kalman filter, while a gated scalar branch estimates stator resistance. Bounded innovation-energy covariance adaptation and the Joseph update maintain numerical consistency, and the resistance-dependent current model is retained in prediction and linearization. A 4.2 s numerical study includes low-speed startup, frequency transitions, load changes, a 52% thermal rise in stator resistance, and speed reversal. Three EAIA-DEKF parameter sets are evaluated under identical data and compared with a fixed-covariance EKF and a current-model MRAS benchmark. The selected set achieves a speed root-mean-square error of 0.2213 rad/s, compared with 2.5112 rad/s for the fixed EKF and 12.3041 rad/s for MRAS. Relative to the fixed EKF, the load-torque and rotor-flux errors decrease by 54.82% and 90.11%, respectively. These results demonstrate bounded and accurate estimation for the investigated deterministic simulation scenario; broader robustness requires repeated-noise, uncertainty, inverter-nonlinearity, and experimental tests.

1. Introduction

Mechanical speed sensors provide direct feedback but increase wiring, alignment, maintenance, and failure points in induction-motor drives. Sensorless operation is therefore attractive where cost, reliability, or environmental constraints discourage mechanical transducers. Classical adaptive speed observers [1], [2] established the field, and very-low-speed operation was subsequently improved by compensating inverter nonlinearities and identifying uncertain parameters [3]. Low stator frequency, load transients, resistance drift, and measurement noise nevertheless continue to reduce observer information.

Kalman-filter research can be grouped into state-observer design and covariance adaptation. Multiple-model EKF observation improves speed and flux estimation [4], whereas adaptive fading, strong tracking, hybrid adaptation, and optimized covariance structures address model mismatch and transient consistency [5], [6], [7], [8], [9], [10]. EKF-UKF comparisons [11] and real-time studies [12], [13] further show that estimation quality depends on covariance selection, numerical implementation, and computational burden.

A second group addresses parameter mismatch. EKF-, UKF-, and iterated-EKF estimators have been reported for resistance, load torque, inertia, and joint parameter estimation [14], [15], [16]–[18], [19], [20]. Observability analyses warn that simultaneous speed and resistance adaptation becomes unreliable when excitation is weak [21], [22]; sliding-mode identification offers an alternative but introduces tuning and chattering issues [23].

A third group emphasizes lower-complexity or application-oriented observers. MRAS methods remain computationally attractive [24], [25], while simplified and all-speed schemes [26], [27], [28], predictive-control observers [29], load-torque estimation [30], and current-sensor-fault compensation [31] improve specific operating conditions. However, the closest adaptive EKF and dual-estimation approaches generally adapt covariance, estimate parameters, or address low-excitation operation separately. The present method coordinates these functions while retaining the resistance-dependent model in both prediction and linearization.

Table 1 distinguishes the proposed structure from the most closely related observer classes. The EAIA-DEKF is not defined by any single mechanism; its novelty is the coordinated sample-by-sample interaction of a six-state filter, a non-augmented resistance branch, excitation-dependent suspension, bounded innovation adaptation, parameter projection, and a Joseph covariance update.

The resulting contributions are: (1) a resistance-dependent prediction model with explicit numerical specialization; (2) a dual state-parameter structure that avoids augmenting a slowly varying resistance into the fast electrical state vector; (3) excitation-gated resistance learning with parameter projection; (4)

bounded covariance adaptation followed by the Joseph posterior update; and (5) a reproducible, objective-weighted comparison with MRAS, fixed EKF, and three EAIA-DEKF settings under identical data.

Table 1: Comparison with closely related observer classes

Observer class	Joint state/parameter estimation	Excitation-aware suspension	Adaptive covariance	Numerically safeguarded update	Main distinction
Fixed-covariance EKF	States only	No	No	Conventional	Low burden; sensitive to resistance drift
Adaptive EKF [6], [8]	Primarily states	No	Yes	Method dependent	Adapts filter statistics
Multi-parameter / dual EKF [16]–[18]	Yes	Generally no	Method dependent	Method dependent	Estimates uncertain motor parameters
Proposed EAIA-DEKF	Six states + scalar stator resistance	Yes	Bounded Q and diagonal R _y	Projection + Joseph form	Coordinates adaptation and low-excitation protection

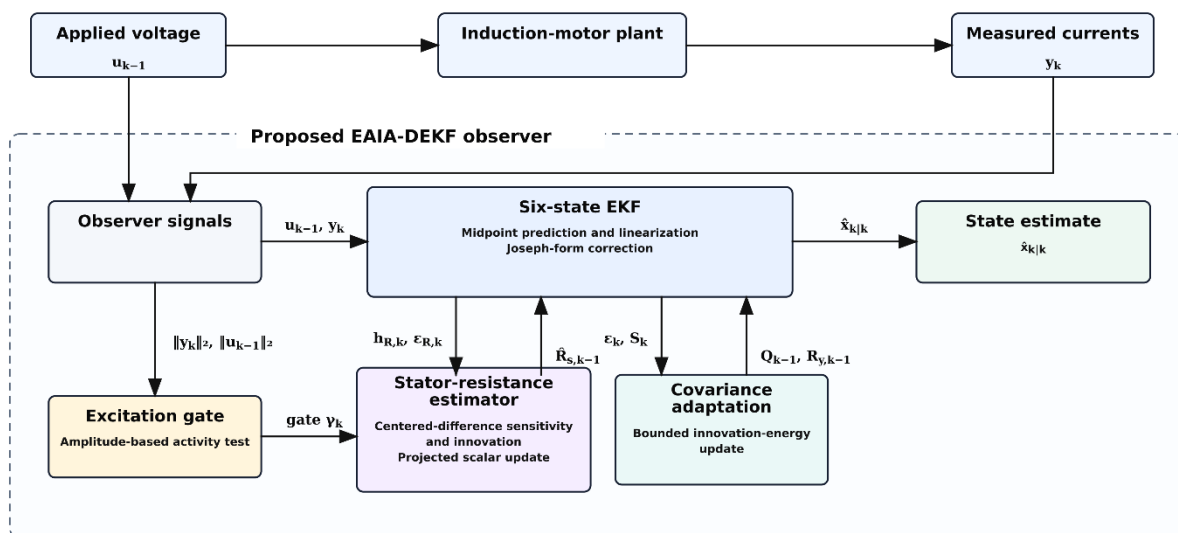


Figure 1: Overall architecture and signal flow of the proposed EAIA-DEKF observer for sensorless induction-motor drives.

2. Methods

The notation used in the model, observer, and evaluation criteria is summarized in Table 2. Closely related quantities are grouped so that symbols need not be redefined repeatedly.

Table 2: Parameter notation used in the induction-motor model and EAIA-DEKF.

Parameter name	Symbol	Unit
Stationary-frame stator-voltage components	v_α, v_β	V
Measured stator-current components	i_α^m, i_β^m	A
Stator-current state components	i_α, i_β	A
Rotor-flux components	ψ_α, ψ_β	Wb
Actual and estimated mechanical speed	$\omega_m, \hat{\omega}_m$	rad/s

Parameter name	Symbol	Unit
Electromagnetic and load torques	$T_e, T_L, \hat{T}_L$	N·m
Stator and rotor resistances	$R_s, R_{s0}, \hat{R}_s, R_r$	Ω
Stator, rotor, and mutual inductances	L_s, L_r, L_m	H
Leakage coefficient and pole-pair number	σ, p	–
Rotor time constant and sampling interval	T_r, T_s	s
Rotor inertia and viscous-friction coefficient	J, B	kg·m ² ; N·m·s/rad
Current-model and torque coefficients	$a_s, b_\psi, c_\omega, g_u, k_T$	mixed SI units
Input, measurement, state, and flux vectors	$\mathbf{u}, \mathbf{y}, \mathbf{x}, \boldsymbol{\psi}$	mixed SI units
State function and discrete transition map	$\mathbf{f}, \Phi$	state-rate; state
State Jacobian, transition, measurement, and Kalman-gain matrices	$\mathbf{A}, \mathbf{F}, \mathbf{H}, \mathbf{K}$	compatible SI units
State, process, measurement, and innovation covariances	$\mathbf{P}, \mathbf{Q}_0, \mathbf{R}_y, \mathbf{S}$	squared compatible units
State and resistance innovations	$\boldsymbol{\varepsilon}, \boldsymbol{\varepsilon}_R$	A
Resistance sensitivity and scalar-branch gain	$\mathbf{h}_R, \mathbf{K}_R$	A/ Ω ; Ω /A
Resistance variance, process variance, perturbation, and bounds	$\pi_R, q_R, \delta_R, R_{s,\min}, R_{s,\max}$	Ω^2 ; Ω^2 ; Ω ; Ω
Excitation thresholds	$I_{\min}, V_{\min}$	A; V
Gate, covariance scale, gains, and forgetting factors	$\gamma, \lambda_Q, \kappa_R, \rho_Q, \rho_R$	–
Evaluation set and principal error measures	$J_e, N_e, \text{RMSE}_\omega, \text{RMSE}_{T_L}, \text{RMSE}_\psi, \text{RMSE}_{R_s}$	–; –; rad/s; N·m; Wb; Ω

2.1. Standardized Induction-Motor Model

The voltage input and measured-current vectors are defined in the stationary $\alpha\beta$ frame.

$$\mathbf{u}_k = \begin{bmatrix} v_{\alpha,k} & v_{\beta,k} \end{bmatrix}^T, \quad \mathbf{y}_k = \begin{bmatrix} i_{\alpha,k}^m & i_{\beta,k}^m \end{bmatrix}^T \quad (1)$$

The electrical and mechanical quantities to be estimated are collected in one six-dimensional state vector.

$$\mathbf{x}_k = \begin{bmatrix} i_{\alpha,k} & i_{\beta,k} & \psi_{\alpha,k} & \psi_{\beta,k} & \omega_{m,k} & T_{L,k} \end{bmatrix}^T \quad (2)$$

The leakage coefficient and rotor time constant follow from the motor parameters.

$$\sigma = 1 - \frac{L_m^2}{L_s L_r}, \quad T_r = \frac{L_r}{R_r} \quad (3)$$

The stator-current dynamics retain the instantaneous stator resistance.

$$\dot{i}_\alpha = -a_s(R_s)i_\alpha + b_\psi\psi_\alpha + c_\omega p\omega_m\psi_\beta + g_u v_\alpha \quad (4)$$

$$\dot{i}_\beta = -a_s(R_s)i_\beta + b_\psi\psi_\beta - c_\omega p\omega_m\psi_\alpha + g_u v_\beta \quad (5)$$

The rotor-flux dynamics complete the electrical subsystem.

$$\dot{\psi}_\alpha = \frac{L_m}{T_r} i_\alpha - \frac{1}{T_r} \psi_\alpha - p\omega_m\psi_\beta \quad (6)$$

$$\dot{\psi}_\beta = \frac{L_m}{T_r} i_\beta - \frac{1}{T_r} \psi_\beta + p\omega_m\psi_\alpha \quad (7)$$

Repeated parameter combinations are represented by compact coefficients.

$$a_s(R_s) = \frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma T_r}, \quad b_\psi = \frac{L_m}{\sigma L_s L_r T_r}, \quad c_\omega = \frac{L_m}{\sigma L_s L_r}, \quad g_u = \frac{1}{\sigma L_s} \quad (8)$$

Electromagnetic torque and mechanical speed are governed by

$$T_e = k_T(\psi_\alpha i_\beta - \psi_\beta i_\alpha), \quad k_T = \frac{3}{2} p \frac{L_m}{L_r} \quad (9)$$

$$\dot{\omega}_m = \frac{T_e - T_L - B\omega_m}{J} \quad (10)$$

The unknown load torque is represented as a slowly varying state.

$$\dot{T}_L = w_T \quad (11)$$

Only the two stator currents are measured.

$$\mathbf{y}_k = \mathbf{H}\mathbf{x}_k + \mathbf{n}_k, \quad \mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad \text{cov}(\mathbf{n}_k) = \mathbf{R}_{y,k} \quad (12)$$

2.2. Numerical Specialization and Discretization

Table 3 contains only the physical induction-motor parameters used in the study. Matrix entries in the following observer settings follow the state order in (2).

Table 3: Physical induction-motor parameters

Parameter	Symbol	Value	Unit
Nominal stator resistance	R_{s0}	1.405	Ω
Rotor resistance	R_r	1.395	Ω
Stator, rotor, and mutual inductances	L_s, L_r, L_m	0.178; 0.178; 0.1722	H
Rotor inertia	J	0.0131	$\text{kg}\cdot\text{m}^2$
Viscous-friction coefficient	B	0.002985	$\text{N}\cdot\text{m}\cdot\text{s}/\text{rad}$
Pole-pair number	p	2	–

The simulation uses $T_s = 5 \times 10^{-4}$ s, $t_f = 4.20$ s, a current-noise standard deviation of 0.08 A, an initial state estimate of $\hat{\mathbf{x}}_{0|0} = [0, 0, 0, 0, 0, 2]^T$, and $\mathbf{P}_0 = \text{diag}(2, 2, 0.3, 0.3, 400, 20)$. The fixed-EKF covariance is $\mathbf{Q}_{\text{fixed}} = \text{diag}(2 \times 10^{-4}, 2 \times 10^{-4}, 2 \times 10^{-6}, 2 \times 10^{-6}, 0.20, 0.010)$, whereas the EAIA-DEKF uses $\mathbf{Q}_0 = \text{diag}(1.5 \times 10^{-4}, 1.5 \times 10^{-4}, 1.5 \times 10^{-6}, 1.5 \times 10^{-6}, 0.12, 0.006)$ and $\mathbf{R}_{y,0} = 0.08^2 \mathbf{I}_2$. The scalar branch is initialized with $\hat{R}_{s,0} = 1.405 \Omega$ and $\pi_{R,0} = 0.25 \Omega^2$, with $\delta_R = 0.00281 \Omega$, $\pi_{R,\min} = 10^{-7} \Omega^2$, a projection interval of $[0.77275, 2.248] \Omega$, a regularizer of 10^{-5}A^2 , and measurement-covariance diagonal limits of $[7.84 \times 10^{-4}, 0.1024] \text{A}^2$. Evaluation begins at 0.35 s. The MRAS speed gain is 0.03, and its torque-smoothing factors are 0.985 and 0.015.

Substitution of the motor parameters gives

$$\sigma = 1 - \frac{0.1722^2}{0.178 \times 0.178} = 0.0641068, \quad T_r = \frac{0.178}{1.395} = 0.1275986 \text{ s} \quad (13)$$

The compact coefficients are evaluated explicitly at the nominal resistance.

$$\begin{aligned} a_{s0} = a_s(R_{s0}) &= 237.5399 \text{ s}^{-1}, \quad b_\psi = 664.4208, \quad c_\omega = 84.7791, \\ g_u &= 87.6347, \quad k_T = 2.90225 \end{aligned} \quad (14)$$

The numerical current equations keep $a_s(R_s)$ variable; only its nominal value is reported in (14).

$$\dot{i}_\alpha = -a_s(R_s)i_\alpha + 664.4208\psi_\alpha + 169.5583\omega_m\psi_\beta + 87.6347v_\alpha \quad (15)$$

$$\dot{i}_\beta = -a_s(R_s)i_\beta + 664.4208\psi_\beta - 169.5583\omega_m\psi_\alpha + 87.6347v_\beta \quad (16)$$

The mechanical equation becomes:

$$\dot{\omega}_m = 221.5456(\psi_\alpha i_\beta - \psi_\beta i_\alpha) - 0.227863\omega_m - 76.3359T_L \quad (17)$$

A midpoint transition is used in both EKF implementations.

$$\Phi(\mathbf{x}_k, \mathbf{u}_k, R_{s,k}) = \mathbf{x}_k + T_s \mathbf{f}\left(\mathbf{x}_k + \frac{T_s}{2} \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k, R_{s,k}), \mathbf{u}_k, R_{s,k}\right) \quad (18)$$

For clarity, the complete α -axis midpoint sequence is expanded below. The same construction applies to the remaining states.

$$\begin{aligned}
g_{\alpha,k} &= -a_s(\hat{R}_{s,k})i_{\alpha,k} + 664.4208\psi_{\alpha,k} + 169.5583\omega_{m,k}\psi_{\beta,k} + 87.6347v_{\alpha,k}, \\
\mathbf{x}_{k+\frac{1}{2}} &= \mathbf{x}_k + \frac{T_s}{2}\mathbf{f}(\mathbf{x}_k, \mathbf{u}_k, \hat{R}_{s,k}), \\
g_{\alpha,k+\frac{1}{2}} &= -a_s(\hat{R}_{s,k})i_{\alpha,k+\frac{1}{2}} + 664.4208\psi_{\alpha,k+\frac{1}{2}} + 169.5583\omega_{m,k+\frac{1}{2}}\psi_{\beta,k+\frac{1}{2}} + 87.6347v_{\alpha,k}, \\
i_{\alpha,k+1} &= i_{\alpha,k} + T_s g_{\alpha,k+\frac{1}{2}}
\end{aligned} \tag{19}$$

Linearization gives the continuous state Jacobian.

$$\mathbf{A} = \begin{bmatrix} -a_s & 0 & b_\psi & c_\omega p\omega_m & c_\omega p\psi_\beta & 0 \\ 0 & -a_s & -c_\omega p\omega_m & b_\psi & -c_\omega p\psi_\alpha & 0 \\ L_m/T_r & 0 & -1/T_r & -p\omega_m & -p\psi_\beta & 0 \\ 0 & L_m/T_r & p\omega_m & -1/T_r & p\psi_\alpha & 0 \\ -k_T\psi_\beta/J & k_T\psi_\alpha/J & k_T i_\beta/J & -k_T i_\alpha/J & -B/J & -1/J \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{20}$$

The discrete transition matrix is approximated at the midpoint.

$$\mathbf{F}_k \approx \mathbf{I}_6 + T_s \mathbf{A}(\mathbf{x}_{k+\frac{1}{2}}^-, \hat{R}_{s,k}) \tag{21}$$

2.3. State-Filter Branch

The fixed-covariance EKF uses the same six-state model but holds $R_s = R_{s0}$, $\mathbf{Q} = \mathbf{Q}_{\text{fixed}}$, and $\mathbf{R}_y = \mathbf{R}_{y,0}$. The EAIA-DEKF state branch uses the latest resistance estimate in both prediction and linearization.

$$\mathbf{x}_{k|k-1} = \Phi(\mathbf{x}_{k-1|k-1}, \mathbf{u}_{k-1}, \hat{R}_{s,k-1}) \tag{22}$$

$$\mathbf{P}_{k|k-1} = \mathbf{F}_{k-1} \mathbf{P}_{k-1|k-1} \mathbf{F}_{k-1}^T + \lambda_{Q,k-1} \mathbf{Q}_0 \tag{23}$$

The innovation covariance uses the measurement covariance available before the current adaptation step.

$$\boldsymbol{\varepsilon}_k = \mathbf{y}_k - \mathbf{H} \mathbf{x}_{k|k-1}, \quad \mathbf{S}_k = \mathbf{H} \mathbf{P}_{k|k-1} \mathbf{H}^T + \mathbf{R}_{y,k-1} \tag{24}$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}^T \mathbf{S}_k^{-1} \tag{25}$$

$$\mathbf{x}_{k|k} = \mathbf{x}_{k|k-1} + \mathbf{K}_k \boldsymbol{\varepsilon}_k \tag{26}$$

The Joseph form is used for the posterior covariance.

$$\mathbf{P}_{k|k} = (\mathbf{I}_6 - \mathbf{K}_k \mathbf{H}) \mathbf{P}_{k|k-1} (\mathbf{I}_6 - \mathbf{K}_k \mathbf{H})^T + \mathbf{K}_k \mathbf{R}_{y,k-1} \mathbf{K}_k^T \tag{27}$$

2.4. Stator-Resistance Identification Branch

Stator resistance is represented by a scalar random walk.

$$\begin{aligned} R_{s,k} &= R_{s,k-1} + w_{R,k-1}, \\ \pi_{R,k|k-1} &= \pi_{R,k-1|k-1} + q_R \end{aligned} \quad (28)$$

A centered perturbation supplies the two-channel current sensitivity.

$$\mathbf{h}_{R,k} = \frac{\mathbf{H}\Phi(\mathbf{x}_{k-1|k-1}, \mathbf{u}_{k-1}, \hat{R}_{s,k-1} + \delta_R) - \mathbf{H}\Phi(\mathbf{x}_{k-1|k-1}, \mathbf{u}_{k-1}, \hat{R}_{s,k-1} - \delta_R)}{2\delta_R} \quad (29)$$

$$\boldsymbol{\varepsilon}_{R,k} = \mathbf{y}_k - \mathbf{H}\Phi(\mathbf{x}_{k-1|k-1}, \mathbf{u}_{k-1}, \hat{R}_{s,k-1}) \quad (30)$$

$$\mathbf{K}_{R,k} = \pi_{R,k|k-1} \mathbf{h}_{R,k}^T \left(\pi_{R,k|k-1} \mathbf{h}_{R,k} \mathbf{h}_{R,k}^T + \mathbf{R}_{y,k-1} + \delta_R \mathbf{I}_2 \right)^{-1} \quad (31)$$

The amplitude-based gate permits learning only when both measured current and applied voltage exceed prescribed thresholds.

$$\gamma_k = \begin{cases} 1, & \|\mathbf{y}_k\|_2 \geq I_{\min} \text{ and } \|\mathbf{u}_{k-1}\|_2 \geq V_{\min} \\ 0, & \text{otherwise} \end{cases} \quad (32)$$

This gate is a practical activity test rather than a formal observability proof. When it is inactive, both the resistance estimate and its posterior information are held consistently.

$$\begin{aligned} \hat{R}_{s,k} &= \begin{cases} \text{proj}_{[R_{s,\min}, R_{s,\max}]}(\hat{R}_{s,k-1} + \kappa_R \mathbf{K}_{R,k} \boldsymbol{\varepsilon}_{R,k}), & \gamma_k = 1 \\ \hat{R}_{s,k-1}, & \gamma_k = 0 \end{cases} \\ \pi_{R,k|k} &= \begin{cases} \max\{\pi_{R,\min}, (1 - \mathbf{K}_{R,k} \mathbf{h}_{R,k}) \pi_{R,k|k-1}\}, & \gamma_k = 1 \\ \pi_{R,k|k-1}, & \gamma_k = 0 \end{cases} \end{aligned} \quad (33)$$

2.5. Covariance Adaptation and Evaluation Criteria

Normalized innovation energy rescales the process covariance and updates the diagonal measurement covariance after the state correction. The updated $\mathbf{R}_{y,k}$ is used at sample $k + 1$.

$$\eta_k = \frac{1}{2} \boldsymbol{\varepsilon}_k^T \mathbf{S}_k^{-1} \boldsymbol{\varepsilon}_k, \quad \lambda_{Q,k} = \text{sat}_{[\lambda_{Q,\min}, \lambda_{Q,\max}]}(\rho_Q \lambda_{Q,k-1} + (1 - \rho_Q) \eta_k) \quad (34)$$

$$\mathbf{R}_{y,k} = \text{diagclip}_{[(0.35\sigma_y)^2, (4\sigma_y)^2]}(\rho_R \mathbf{R}_{y,k-1} + (1 - \rho_R) \boldsymbol{\varepsilon}_k \boldsymbol{\varepsilon}_k^T)$$

Accuracy is evaluated after the 0.35 s initialization interval.

$$\begin{aligned}
\text{RMSE}_\omega &= \sqrt{\frac{1}{N_e} \sum_{k \in I_e} (\hat{\omega}_{m,k} - \omega_{m,k})^2}, \\
\text{RMSE}_{T_L} &= \sqrt{\frac{1}{N_e} \sum_{k \in I_e} (\hat{T}_{L,k} - T_{L,k})^2}, \\
\text{RMSE}_\psi &= \sqrt{\frac{1}{N_e} \sum_{k \in I_e} \|\Psi_k - \psi_k\|_2^2}, \\
\text{RMSE}_{R_s} &= \sqrt{\frac{1}{N_e} \sum_{k \in I_e} (\hat{R}_{s,k} - R_{s,k})^2}, \\
e_{\omega, \max} &= \max_{k \in I_e} |\hat{\omega}_{m,k} - \omega_{m,k}|, \\
\bar{\eta} &= \frac{1}{N_e} \sum_{k \in I_e} \eta_k
\end{aligned} \tag{35}$$

2.6. Benchmark Observers and Simulation Protocol

The plant is integrated with fourth-order Runge-Kutta, whereas the fixed EKF and EAIA-DEKF use (18). The input angle is obtained by integrating the commanded electrical frequency, and the voltage magnitude is limited according to $\text{clip}(18 + 4.85|f|, 18, 260)$ V. A deterministic twelve-tone RMS-normalized multisine is added to each current channel using the same realization for all observers. The operating transitions are implemented with smooth hyperbolic-tangent profiles so that the plant does not receive artificial discontinuities.

The current-model MRAS benchmark propagates the four electrical states with nominal and updates speed by a normalized finite-difference current-sensitivity gradient with gain 0.03. Its load-torque estimate is reconstructed from the electromagnetic-torque balance and low-pass filtered using the factors in Table 3. This description matches the numerical benchmark used to generate Table 7.

Three EAIA-DEKF settings are evaluated without changing the plant, measurements, initial state, or noise realization. Selection uses a prespecified normalized multiobjective score: speed RMSE and maximum speed error receive weights 0.50 and 0.25, while load-torque, rotor-flux, and stator-resistance RMSE receive 0.10, 0.075, and 0.075. Each metric is divided by the best value among Sets A-C (table 4), so the theoretical lower bound is 1. The resulting scores are 2.2872, 1.0087, and 1.2585 for Sets A, B, and C, respectively. Set B is therefore selected because the 75% combined priority assigned to speed behavior outweighs Set C's small secondary-error advantages.

Table 4: EAIA-DEKF parameter sets.

Set	ρ_Q	ρ_R	κ_R	$q_R (\Omega^2)$	$I_{\min} (\text{A})$	$V_{\min} (\text{V})$	λ_Q limits
A	0.990	0.997	0.55	1.2×10^{-6}	1.2	30	0.35–6
B	0.985	0.995	0.70	2.0×10^{-6}	1.0	25	0.25–8
C	0.970	0.990	0.85	3.5×10^{-6}	0.8	20	0.20–10

Table 5: Operating scenario.

Interval (s)	Frequency command	Load torque	Stator resistance
0–0.45	8 Hz startup	1.5 N·m	nominal
0.45–1.45	35 Hz	1.5–6 N·m	nominal
1.45–2.25	18 Hz	6–9 N·m	thermal rise begins
2.25–3.15	42 Hz	9 N·m	approaches +52%
3.15–4.20	–26 Hz reversal	9–4 N·m	+52%

2.7. Computational Complexity and Real-Time Feasibility

All Kalman inversions are only 2×2 because two currents are measured; the resistance branch adds a scalar update rather than enlarging the state covariance. Relative to the fixed EKF, EAIA-DEKF retains one 6×6 covariance propagation and one 2×2 innovation inversion, but adds two perturbed model transitions for the centered resistance sensitivity, one scalar gain/update, diagonal covariance adaptation, gating, clipping, and projection. Thus, its dominant matrix dimension remains six and memory remains $O(6^2)$, while the extra model evaluations make the expected per-sample workload approximately three state-transition evaluations instead of one. MRAS remains the least expensive benchmark because it propagates four electrical states without a covariance matrix. At $T_s = 0.5$ ms, practical deployment requires the complete update to finish within 500 μs ; execution time was not benchmarked on target hardware in this numerical study, so real-time feasibility is structural rather than experimentally verified.

Table 6: Computational structure of the compared observers.

Observer	State/model work per sample	Largest inversion	Covariance storage	Relative burden
MRAS	Four-state model + normalized adaptation	None	None	Low
Fixed EKF	One six-state transition + covariance update	2×2	6×6	Moderate
EAIA-DEKF	Three six-state transitions + EKF + scalar branch/adaptation	2×2 + scalar	6×6 + scalar	Higher than fixed EKF; same dominant dimension

3. Results and Discussion

3.1. Speed Estimation

Figure 2 compares the true speed and the three estimates over the complete cycle. MRAS oscillation after the first acceleration indicates that its normalized adaptation cannot fully reject the combined frequency and load transitions. The fixed EKF is accurate on quasi-steady intervals, but its error grows as the actual stator resistance departs from the nominal model, showing a systematic model-mismatch effect rather than random scatter. EAIA-DEKF Set B remains close to the true trajectory because the resistance branch reduces this bias and covariance scaling temporarily increases state correction when innovation energy rises.

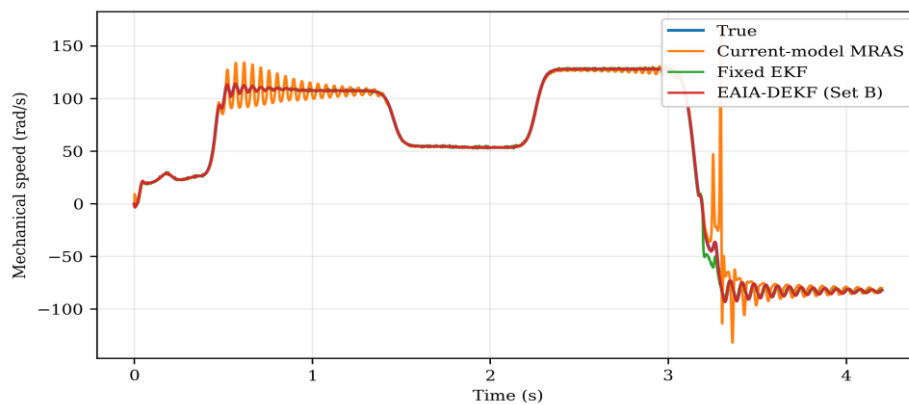


Figure 2: True and estimated mechanical speed over the complete operating cycle.

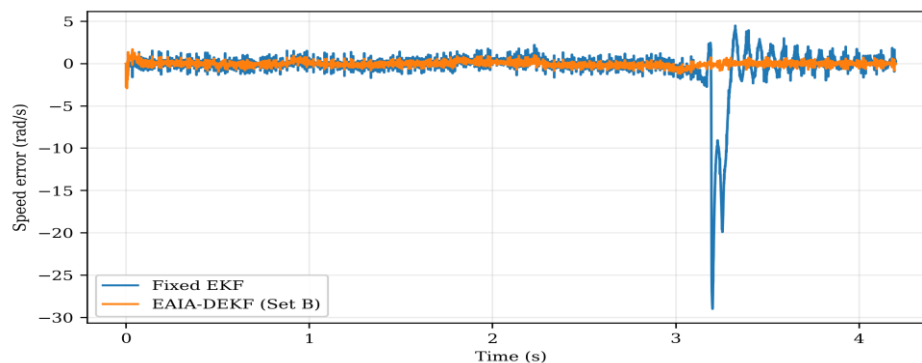


Figure 3: Speed-estimation errors of the fixed EKF and EAIA-DEKF Set B.

Figure 3 isolates the fixed-EKF and EAIA-DEKF speed errors. The fixed EKF reaches 28.9855 rad/s, whereas Set B limits the maximum error to 1.2230 rad/s. The corresponding speed RMSE values are 2.5112 and 0.2213 rad/s, a reduction of 91.19%; relative to MRAS, the reduction is 98.20%. The largest separation occurs around reversal, where simultaneous sign change, load evolution, and resistance mismatch challenge the nominal model. Set B's bounded peak shows that covariance adaptation improves transient correction without persistent inflation.

3.2. Load Torque, Rotor Flux, and Stator Resistance

Figure 4 shows that Set B follows the load transitions without the large negative excursion of the fixed EKF during reversal. Load-torque RMSE decreases from 1.2385 to 0.5595 N·m. Because load torque is represented as a slowly varying state, sharp changes cannot be followed instantaneously; the remaining lag is therefore consistent with the process model rather than estimator divergence.

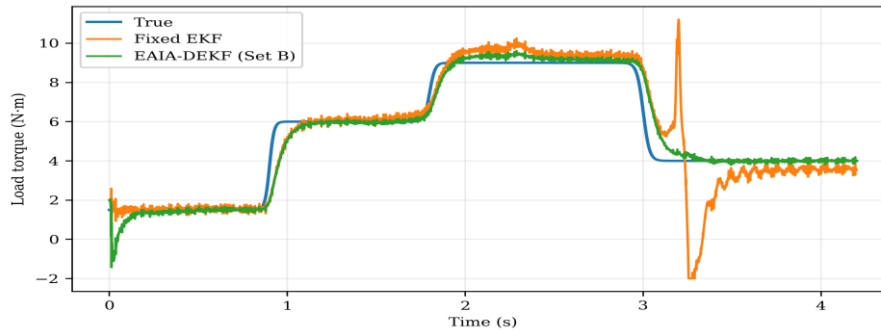


Figure 4: True and estimated load torque.

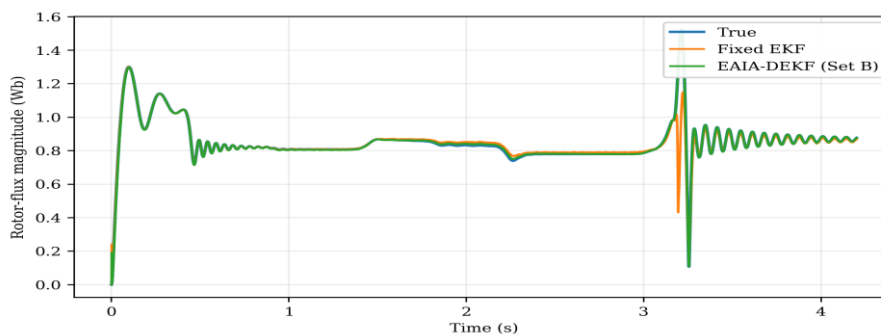


Figure 5: True and estimated rotor-flux magnitude.

The rotor-flux magnitude in Figure 5 recovers rapidly after startup and reversal. Vector-flux RMSE decreases from 0.07627 to 0.00754 Wb. This reduction is important because the torque and speed channels depend on the cross-product of current and flux; improved flux consistency consequently limits the mechanical-state error during transients.

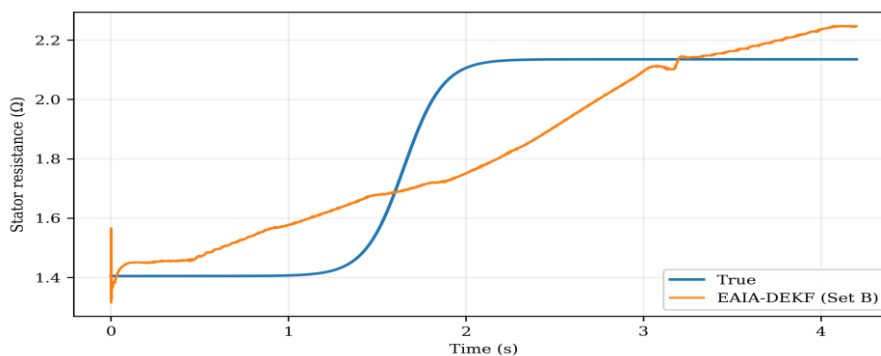


Figure 6: Thermal stator-resistance variation and the Set B estimate.

Figure 6 presents the thermal resistance profile and the Set B estimate. The resistance RMSE is 0.17389Ω . The residual final bias is an intended trade-off: the gate suppresses poorly conditioned parameter updates when voltage or current amplitude is insufficient, preventing noise-driven resistance motion but slowing convergence. Accordingly, the result supports bounded estimation in the tested excitation pattern, not uniform resistance identifiability at arbitrary low excitation.

3.3. Influence of the Three Adaptation Settings

Figure 7 compares the moving RMS speed error. Set A is conservative and produces the largest reversal peak. Set C adapts more rapidly but increases the maximum speed error to 2.2036 rad/s . Set B gives the lowest speed RMSE and peak error, reducing speed RMSE by 43.41% relative to Set A and by 10.38% relative to Set C. The weighted score reported in Section 2.6 formalizes this preference: Set C slightly improves secondary estimates, whereas Set B provides the best compromise for a speed-control application.

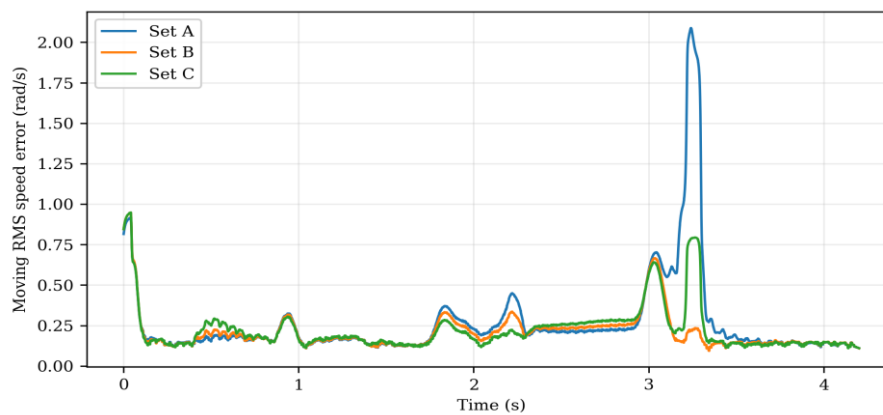


Figure 7: Moving RMS speed error for the three EAIA-DEKF parameter sets.

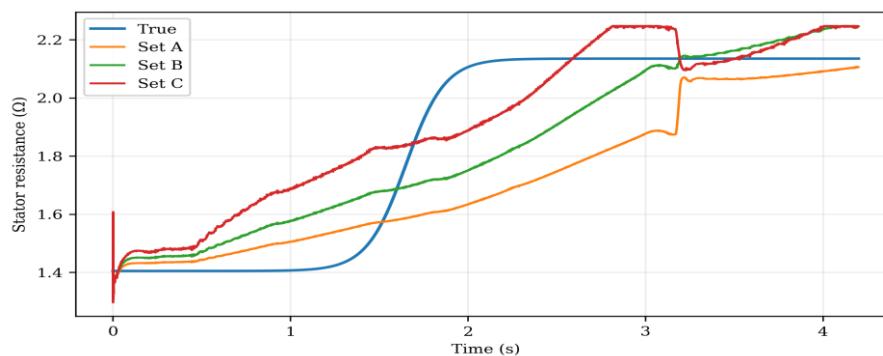


Figure 8: Stator-resistance estimates for the three parameter sets.

Figure 8 shows the corresponding resistance estimates. Set C gives a slightly smaller resistance RMSE than Set B, but its lower gate thresholds and larger adaptation gain also transmit stronger parameter corrections into the speed channel. Its larger speed peak therefore demonstrates why minimum resistance RMSE alone is not an appropriate tuning objective.

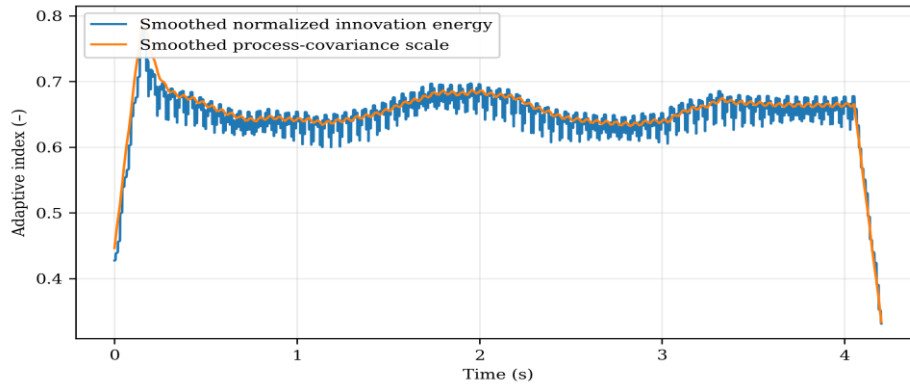


Figure 9: Smoothed normalized innovation energy and process-covariance scale.

The curves in Figure 9 are smoothed only for visualization by a 0.30 s moving average; the algorithm uses the unsmoothed quantities in (34). The process scale remains bounded and mostly below unity. Short departures follow operating transitions, while its return toward the nominal range indicates temporary statistical correction rather than continuous covariance inflation or loss of numerical consistency.

3.4. Current Consistency and Reversal Response

Figure 10 is a local consistency check between the measured α -axis current and reconstructed current state. Their close agreement confirms that the posterior state remains compatible with the measured channel. It is not an independent validation, because the same current enters the EKF correction, and it should not be interpreted as experimental evidence.

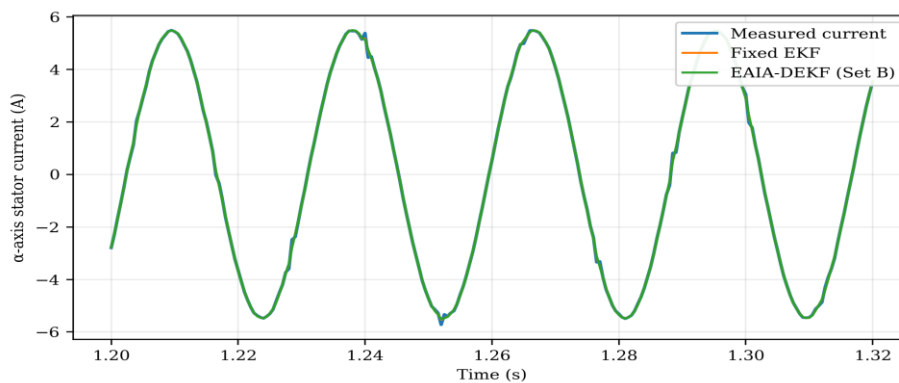


Figure 10: Measured and reconstructed α -axis stator current.

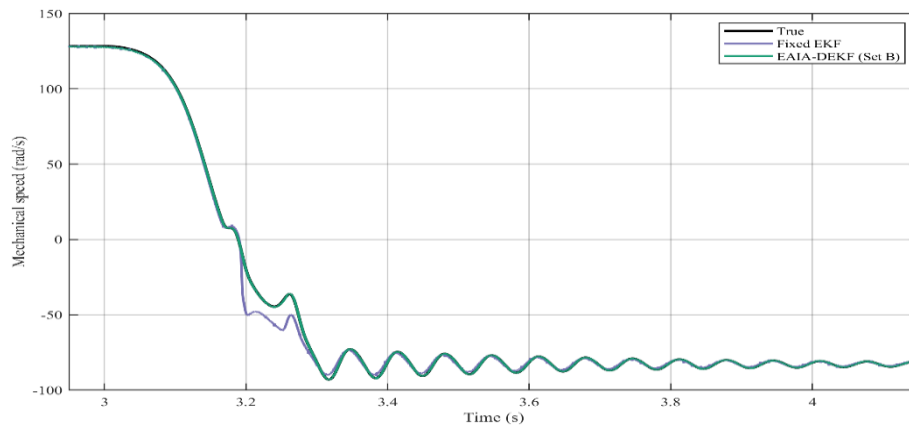


Figure 11: Detailed mechanical-speed response during reversal.

Figure 11 focuses on reversal. Set B crosses zero speed without divergence and settles rapidly on the negative-speed trajectory, whereas the fixed EKF shows a much larger transient. Zero crossing is particularly demanding because back-EMF information weakens and changes sign; the bounded response is attributable to coordinated state, parameter, and covariance updates under this specific simulated excitation.

Table 7: Quantitative comparison

Metric	MRAS	Fixed EKF	Set A	Set B	Set C
Speed RMSE (rad/s)	12.3041	2.5112	0.3911	0.2213	0.2470
Load-torque RMSE (N·m)	2.2542	1.2385	0.6204	0.5595	0.5519
Rotor-flux RMSE (Wb)	–	0.07627	0.01556	0.00754	0.00705
Stator-resistance RMSE (Ω)	–	–	0.24296	0.17389	0.16905
Maximum speed error (rad/s)	–	28.9855	4.9792	1.2230	2.2036
Mean normalized innovation energy (–)	–	–	0.6618	0.6567	0.6836

The results support simultaneous electrical, mechanical, and resistance estimation without a mechanical speed sensor for the specified deterministic scenario (table 5). The improvement is associated with the coordinated state filter, resistance branch, excitation gate, and bounded covariance adaptation rather than a single aggressive gain. However, this evidence uses one noise realization and an idealized numerical inverter. It does not establish statistical robustness to repeated noise, parameter distributions, dead time, saturation, sensor bias, quantization, or unmodeled disturbances.

4. Conclusion

An excitation-aware dual Kalman observer has been developed for sensorless induction-motor drives using consistent $\alpha\beta$ notation. The six-state EKF estimates stator current, rotor flux, mechanical speed, and load torque, while a gated scalar branch identifies stator resistance. The resistance-dependent coefficient is retained in prediction and linearization, and covariance updates follow a non-

circular sample order. In the investigated scenario, Set B achieves a speed RMSE of 0.2213 rad/s and a maximum error of 1.2230 rad/s. Relative to the fixed EKF, speed, load-torque, and rotor-flux RMSE decrease by 91.19%, 54.82%, and 90.11%, respectively. These conclusions are limited to numerical validation with one deterministic noise realization. During low excitation, resistance adaptation is deliberately suspended; this protects numerical stability but can preserve parameter bias and delay reconvergence. Future work will quantify Monte Carlo uncertainty, inverter dead time and saturation, sensor bias and quantization, parameter perturbations, execution time on embedded hardware, and experimental drive performance.

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