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Low-Complexity Recursive NARX for Discriminating Incipient Stator Inter-Turn Short Circuits from Load Variations in Three-Phase Induction Motors

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Abstract

Early detection of stator inter-turn short circuits (ITSCs) is difficult when diagnostic variables also respond to load changes. This study evaluates a low-complexity model-based strategy for separating incipient ITSCs from operating-point variation in a three-phase induction motor. Consistently high-quality data are generated using a physics-based symmetric dq model, with electrical parameters obtained from standard tests. A deliberately low-order polynomial NARX surrogate is then selected, and its four-term deterministic structure is frozen. Rather than serving as a high-fidelity simulator, the surrogate acts as a dynamic-change detector: departures from the nominal motor dynamics are forced to manifest as changes in recursive coefficients. An auxiliary static characteristic adapts the model gain to the operating point. Experimental three-phase voltage and current data from seven repeated tests per condition include ITSCs involving approximately 1.5% and 3% of one stator phase, as well as 48.5% variation in load current. The nonlinear model provides about 22% lower free-run validation error than the corresponding linear model, while static-gain adaptation clearly improves fault/load discrimination. Local linearization relates coefficient drift to effective pole/zero movement. The online estimator uses four coefficients and a 4×4 covariance matrix, requires no matrix inversion, FFT, or trained classifier, and operates sample by sample at the experimental 1-kHz rate. The observed approximately 1.2s response is therefore dominated by evidence accumulation rather than computational execution, supporting embedded condition-monitoring implementation.

Keywords: Induction motor, inter-turn short circuit, fault diagnosis, nonlinear system identification, NARX model, recursive parameter estimation

1 Introduction

Three-phase induction motors (TIMs) are workhorse assets in industrial production, pumping, ventilation, compression, material handling, and transportation. Their reliability is therefore

a production issue as much as an electrical-machine issue: a motor fault can propagate into process interruption, quality losses, emergency maintenance, and collateral damage to connected equipment. Stator inter-turn short circuits (ITSCs) are especially important because a defect

that initially involves only a few turns can produce a localized circulating current, accelerate insulation degradation, and evolve into a more destructive phase-to-phase or phase-to-ground failure [3, 5, 11].

The diagnostic challenge is not merely to identify an already developed fault. For predictive maintenance, the useful target is the *incipient* stage, when the machine is still operating and corrective action can be scheduled. At the same time, an industrial detector must remain robust to legitimate changes in load, supply, speed, and operating point. A sensitive indicator that responds equally to load variation and insulation degradation has limited operational value because it can generate false alarms or force conservative thresholds that hide early faults.

This paper develops the original master’s research [21] and a preliminary conference contribution [20] into a substantially broader journal analysis. The study is reorganized around the specific engineering question of whether incipient ITSCs can be separated from a large benign load variation using a low-order, interpretable model that can operate recursively. A central methodological point is made explicit here: the online model is *not* designed as a reduced digital twin whose primary objective is minimum free-run simulation error. A physics-based motor model is used upstream to generate persistently exciting healthy data; the identified surrogate is then deliberately kept small and its structure frozen, so that fault-induced changes in the motor dynamics must be absorbed as changes in the recursive coefficients.

The main contributions are: (i) a transparent physics-to-surrogate identification pathway; (ii) comparison of linear and nonlinear identified models; (iii) a local pole/zero interpretation of the recursive coefficient drift; (iv) explicit ablation of the static-gain adaptation mechanism; (v) experimental evaluation of ITSCs involving approximately 1.5% and 3% of the turns of one stator phase against a 48.5% load-current variation; (vi) analysis of the forgetting-factor trade-off among sensitivity, variance, and detection delay; (vii) phase-wise analysis showing why all three phases should be monitored; and (viii) an industrial implementation assessment contrasting the proposed four-parameter recursive estimator with recent signal-processing, machine-learning, and digital-twin approaches.

2 Industrial Motivation and Recent Advances

2.1 Scale of motor-driven systems and the cost of downtime

The industrial relevance of early fault detection follows from the scale of motor-driven systems. The U.S. Motor System Market Assessment estimates there are 52 million motor systems in the industrial and commercial sectors and reports that motor-driven systems account for about 29% of national electricity use [18]. The same assessment found that 47% of industrial motor systems operate below 75% of full load, emphasizing that substantial operating-point variation is normal rather than exceptional [18]. In Europe, the predecessor ecodesign regulation for single-speed TIMs alone covered an estimated stock of 88 million motors consuming about 903 TWh in 2020; the broader current regulation covers approximately 380 million electric motors and 1,326 TWh of annual electricity use [8]. These figures place induction-motor condition monitoring within a very large installed industrial asset base rather than a niche diagnostic problem.

Unexpected stoppage costs are application-dependent, but the Siemens/Senseye 2024 industry survey estimates 27 h of unplanned downtime per month for an average large plant in the surveyed sectors and about US\$253 million in annual losses; estimated hourly losses ranged from about US\$36,000 in fast-moving consumer goods to US\$2.3 million in automotive manufacturing [22]. Although these survey figures do not constitute a universal cost model, they highlight the importance of early deterioration detection as an operational target, enabling emergency stops to be converted into planned maintenance.

2.2 Recent approaches to incipient inter-turn fault diagnosis

Recent ITSC research can be grouped into four overlapping families: direct electrical signatures and sequence components, time–frequency or transformed features, model/observer-based residuals or parameter estimates, and machine-learning/deep-learning classifiers. Recent examples include robust adaptive parameter tracking [23], current spectrograms [9], STLSP-based

online diagnosis under nuisance conditions [2], voltage–current loci [7], and neural diagnosis from inverter switching statistics [16]. More recent learning-oriented studies use current-space-vector features [19], EfficientNetV2 representations [14], lightweight 1D-ResNet models [15], and ANN/LSTM/physics-informed networks [1], while online digital-twin approaches provide richer residual and localization information [6]. DOI metadata for these recent references were checked against publisher or DOI-indexed records during manuscript preparation.

The literature demonstrates increasingly accurate diagnosis but also a practical trade-off. High-capacity learned and digital-twin representations can extract rich fault information, whereas current-domain and low-dimensional model-based methods preserve stronger physical interpretability and simpler online execution. The gap addressed here is narrower and explicitly industrial: discriminating a very small ITSC from a substantial normal load change using terminal voltage/current measurements and a low-dimensional recursive model whose operating-point gain is adapted online.

2.3 Computational burden, sampling rate, and embedded feasibility

A particularly useful property of the proposed monitor is that the *online* recursive estimator does not invert a matrix. Although batch least squares typically requires solving the normal equations or an equivalent factorization problem, this computation is performed exclusively during the offline model-design stage. Once the four-regressor NARX structure is established, the recursive covariance update described in Section 4 becomes a rank-one recursion. At each sample, the only normalization required by the RLS core is through the scalar denominator

$$d(k) = \lambda + \boldsymbol{\psi}^T(k)\mathbf{P}(k-1)\boldsymbol{\psi}(k), \quad (1)$$

so no 4×4 inverse is evaluated online. This distinction is important for embedded deployment because the execution path features fixed dimensions, deterministic memory usage, and $O(p^2)$ arithmetic complexity with $p = 4$. This contrasts

with the $O(p^3)$ computational cost and numerical stability challenges associated with repeated inversion of dense matrices.

For each monitored phase, the core persistent state consists of four coefficients and the 4×4 covariance matrix (20 floating-point values), plus short input/output histories and the scalar gain correction. An efficient, symmetry-preserving implementation of Eqs. (1) and the RLS recursions requires only a few tens of scalar multiply–accumulate operations and scalar divisions per sample. Even a conservative direct implementation remains below one hundred elementary multiply/add operations per phase and sample. This is an *analytical operation-count estimate*, not a measured hardware benchmark. At the experimental sampling frequency of 1 kHz, three parallel phase monitors therefore remain in a sub-mega-operation-per-second arithmetic regime, excluding ADC handling and communications. In single-precision arithmetic, the coefficient vector and a full covariance matrix occupy only 80 bytes per phase; even with short histories and working variables, the estimator state is small compared with the memory available in contemporary industrial microcontrollers.

The 1 kHz rate used in the experiments provides approximately 16.7 samples per 60-Hz electrical cycle. Importantly, this rate is not being proposed as a general spectral-analysis requirement: the detector operates directly in the time domain and was identified and validated at this sampling rate for the grid-fed machine studied here. The observed diagnostic delay of approximately 1.2 s corresponds to about 1,200 samples or 72 supply cycles. That interval is governed primarily by the number of samples required for the recursive detector to accumulate sufficient statistical evidence to reliably distinguish a small fault from normal variability, rather than by the computational time required to update the detector. The method should therefore be interpreted as an early condition-monitoring/predictive-maintenance layer. Conventional protection remains essential for developed faults, but it is not intended to diagnose the small terminal-current changes of the incipient ITSC stage addressed here; the two functions are

complementary [3, 5]. Inverter-fed/PWM operation would require new sampling, filtering, model-design, and validation studies before the same rate could be generalized.

Embedded motor diagnosis is already realistic. Pietrzak et al. [17] implemented ITSC symptom extraction on an STM32L476RG ARM Cortex-M4 at 4 kHz; Tarchała et al. [24] explicitly sought to avoid the burden of online FFT analysis; and embedded-oriented studies combine DWT/ML [10], neural inference [4], or spectral estimation with fuzzy logic [12]. Table 1 therefore compares structures rather than claiming cross-platform runtime superiority.

This architecture is consequently amenable to implementation on a DSP, industrial microcontroller, PLC-class edge controller, smart protection relay, or dedicated condition-monitoring module. It also supports a retrofit strategy: voltage and current signals already available in drives, protection systems, or existing transducers can feed three parallel phase-wise estimators, while only parameter trends or an alarm state need to be forwarded to the PLC/SCADA layer. The remaining step needed to convert this feasibility argument into a quantitative embedded claim is a target-hardware benchmark reporting worst-case execution time, memory footprint, numerical precision, and event-level detection latency.

3 Experimental Setup and Fault Scenarios

3.1 Test bench and instrumented motor

The experimental data were obtained from a dedicated induction-motor test bench at the Federal University of São João del-Rei. The rig comprised a three-phase squirrel-cage induction motor mechanically coupled to a DC generator, a resistive load bank, a short-circuit current limiting resistor bank, a variable autotransformer, an acquisition system, and a computer running a LabVIEW-based virtual instrument. Figure 1 shows the experimental bench used for the controlled fault and load-change tests, including the motor-generator set and the externally accessible stator-winding taps.

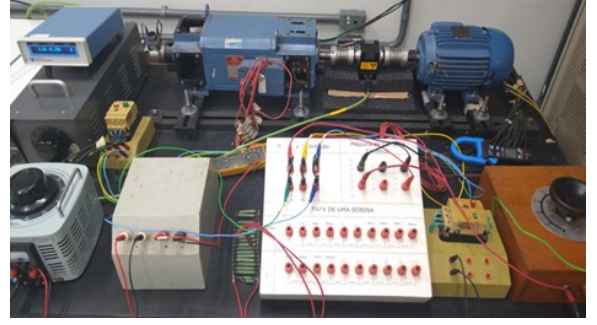


Fig. 1 Experimental test bench for voltage and current acquisition, with accessible stator-winding taps for controlled inter-turn short-circuit tests.

The induction motor has a rated power of 3 cv, a rated voltage of 220 V, a rated current of 9 A, and a rated frequency of 60 Hz, with a four-pole configuration. The motor has a locked-rotor current-to-rated-current ratio of $I_p/I_n = 5.4$, a rated power factor of $\cos \phi = 0.84$, and a nominal efficiency of approximately 78%. Each phase winding consists of six coils, with 33 turns per coil, resulting in a total of 198 turns per phase. External taps were incorporated into the windings to enable the controlled introduction of inter-turn short-circuit faults involving as few as three turns. A resistor bank was connected in series with the faulted turns to limit the resulting circulating current and prevent the experimentally induced fault from developing into a solid short circuit. This configuration enabled the controlled reproduction of incipient inter-turn faults while maintaining the fault severity within the desired experimental range.

3.2 Operating scenarios

Phase voltages V_a, V_b, V_c and currents I_a, I_b, I_c were monitored. Seven repeated tests were conducted for each operating condition. For both fault scenarios, the motor initially operated in steady state at a line current of approximately 6.12 A; after about 5 s, the controlled ITSC was introduced. The first fault involved three of the 198 turns of one phase (approximately 1.5%), and the second involved six turns (approximately 3%). A separate load-change scenario started at 4.12 A and changed to 6.12 A, corresponding to an increase of approximately 48.5%. Thus, the three discrimination cases were 1.5% ITSC (3 shorted

Table 1 Embedded/real-time perspective relative to representative ITSC approaches. “Online burden” is structural and not a cross-platform timing benchmark.

Study	Signals / sampling	Online processing	Implementation evidence	Contrast with this work
This work	Phase v/i ; 1 kHz	Four-regressor NARX; inversion-free RLS; scalar gain update	Experimental detection; hardware timing not yet benchmarked	Sample-wise $p = 4$, $O(p^2)$ update; no FFT, window, optimizer, or trained classifier; about 1.2-s evidence delay.
Tarchala et al. [24]	Drive current/reference vectors	Modified triple Park transform	Experimental drive tests	Avoids online FFT but requires drive-control reference signals.
Guerreiro Carvalho Cunha et al. [10]	Axial leakage flux	DWT/MRA + features + ML	Embedded/field-oriented design	Windowed multistage feature extraction/classification.
Bazan et al. [4]	Phase currents	Mutual information + MLP	Embedded hardware demonstrated	Requires feature extraction, supervised training, and neural inference.
Pietrzak et al. [17]	Axial-flux coil; 4 kHz	ADC + FFT-based symptoms	STM32L476RG Cortex-M4	Hardware feasibility benchmark, but added sensor and spectral processing.
Kouadria et al. [12]	Current; 3 kHz	Root-Prony + fuzzy inference	Experimental validation	Efficient alternative, but includes spectral estimation and fuzzy logic.

turns), 3% ITSC (6 shorted turns), and a benign 4.12-to-6.12-A load-current transition.

Figure 2 translates the method into an industrial signal-flow architecture. The measured phase voltages and currents are separated into three phase-wise channels and processed sample by sample by identical low-order recursive NARX estimators. Static-gain adaptation acts locally in each channel to absorb benign operating-point changes, whereas the coefficient trajectories provide the diagnostic information. Only the compact parameter trends or the final alarm/health state need to be communicated to the supervisory layer; the white-box model and batch structure-selection procedure are offline design steps and are not part of the embedded online computation.

4 From the Physics-Based Motor Model to a Minimal Diagnostic Surrogate

4.1 White-box reference model and generation of healthy data

The identification procedure was initialized using a physics-based reference model of the induction motor, rather than relying on an arbitrarily selected measured dataset. The healthy machine was represented by the conventional symmetric dq model obtained from the electrical equations of the stator and squirrel-cage rotor after Park transformation [3, 13]. In compact form, the model can be written as

$$\mathbf{v}_s = R_s \mathbf{i}_s + \dot{\boldsymbol{\psi}}_s + \boldsymbol{\Omega}_s(\omega) \boldsymbol{\psi}_s, \quad (2)$$

$$\mathbf{0} = R_r \mathbf{i}_r + \dot{\boldsymbol{\psi}}_r + \boldsymbol{\Omega}_r(\omega - \omega_r) \boldsymbol{\psi}_r, \quad (3)$$

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

$$J\dot{\omega}_r = T_e - T_L, \quad (5)$$

where the dq cross-coupling matrices $\boldsymbol{\Omega}_s$ and $\boldsymbol{\Omega}_r$ account for the selected reference-frame speed, and the electrical parameters retain their physical meaning. The asymmetric fault model used in the original study is derived from this symmetric formulation by explicitly modifying the stator resistance and leakage-inductance matrices as a function of the fraction of shorted turns [3, 21].

The equivalent-circuit values used in the healthy simulation are summarized in Table 2. They were the same parameter values adopted for the laboratory motor, allowing the white-box model to serve as a physically grounded generator of normal-operation dynamics rather than as an abstract synthetic benchmark.

Table 2 Electrical parameters of the white-box induction-motor model.

Parameter	Value (Ω)
Stator resistance R_s	2.9115
Stator leakage reactance X_{ls}	3.3928
Rotor resistance R_r	1.6975
Rotor leakage reactance X_{lr}	2.0357
Magnetizing reactance X_m	71.0607

To expose the dynamic modes required for identification, the simulated line voltage was excited with a pseudo-random binary sequence (PRBS). Phase voltage and phase current were then used as the input-output pair. The resulting record contained 1642 samples; the first 822

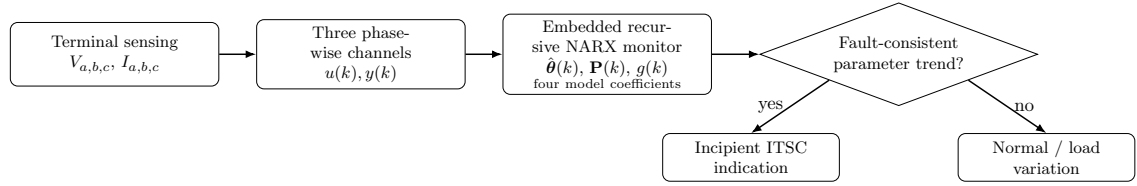


Fig. 2 Industrial deployment of the strategy using three phase-wise recursive NARX estimators with static-gain adaptation and plant control/SCADA integration.

samples were used for structure/parameter estimation and the remaining 820 for independent validation [21]. Figure 3 summarizes this physics-to-diagnostic-model pathway.

Figure 4 documents the two checks that precede online fault tracking. Panel (a) shows the physically generated phase-voltage/phase-current pair used for identification and independent validation; the PRBS excitation ensures that the nominal dynamics needed by the surrogate are present in the data. Panel (b) compares the independent validation signal with the free-run NARX simulation. The RMSE of 0.5860, approximately 22% below that of the corresponding linear model, confirms that the four-term nonlinear structure is dynamically adequate. Importantly, this validation is not the final diagnostic objective: once the structure is frozen, the information of interest is the event-related movement of its coefficients when experimental motor dynamics depart from the nominal condition.

4.2 Why a minimal fault-sensitive model rather than a high-fidelity simulator

The identified model was purposely selected under a different objective from that of a simulation model or digital twin. The model-selection procedure retained candidates that achieved a suitable balance between validation performance, structural simplicity, and the capability to capture parameter variations associated with faulty operating conditions [21]. Therefore, free-run validation was used as a *necessary adequacy check*: the nominal model must capture the essential healthy dynamics to provide a stable reference for its coefficients. It was not necessary, however, to reproduce every motor mode with the minimum achievable simulation error. Adding regressors solely to improve waveform reconstruction would increase online memory and arithmetic cost and,

more importantly, could allow the model structure itself to absorb dynamics that are useful as diagnostic evidence.

The diagnostic mechanism relies on *structure freezing*. The regressor set is selected once from healthy operation. During monitoring, no new terms are added when the motor changes. An incipient ITSC perturbs physical quantities such as winding resistance, leakage/mutual coupling, and the resulting electromechanical dynamics. These perturbations need not create a unique new spectral line; for stator ITSCs, changes in the amplitudes of existing spectral components can also be important. In either case, the effective dynamic modes are reflected in the relationship linking terminal voltage and current change. Because the recursive model cannot adapt its structure, this mismatch is absorbed by the coefficient vector $\hat{\theta}(k)$. Parameter drift is therefore the intended output of the detector, rather than an unwanted identification error.

4.3 Batch identification and fixed-structure NARX representation

Let $u(k)$ denote the phase voltage and $y(k)$ the corresponding phase current. A polynomial NARMAX model was first identified from the healthy data generated by the white-box model. The selected second-order structure comprised four deterministic terms and resulted from the joint use of the Akaike information criterion and the error-reduction-ratio structure-selection procedure, with an explicit preference for low complexity and sensitivity to fault-related data. After batch identification, the stochastic terms were neglected, yielding the following deterministic NARX model:

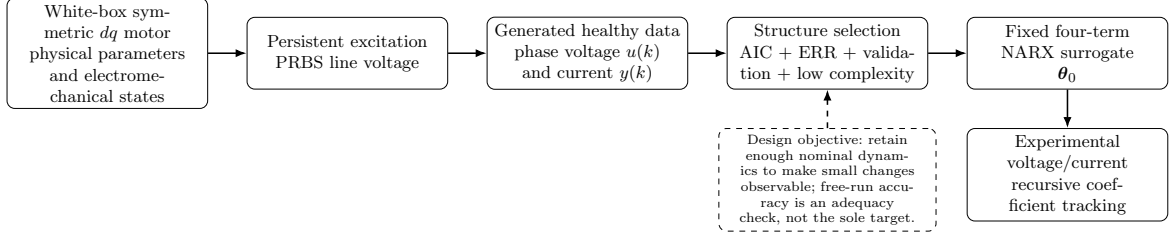


Fig. 3 Physics-based model to low-order diagnostic surrogate with frozen NARX structure and recursive coefficient tracking.

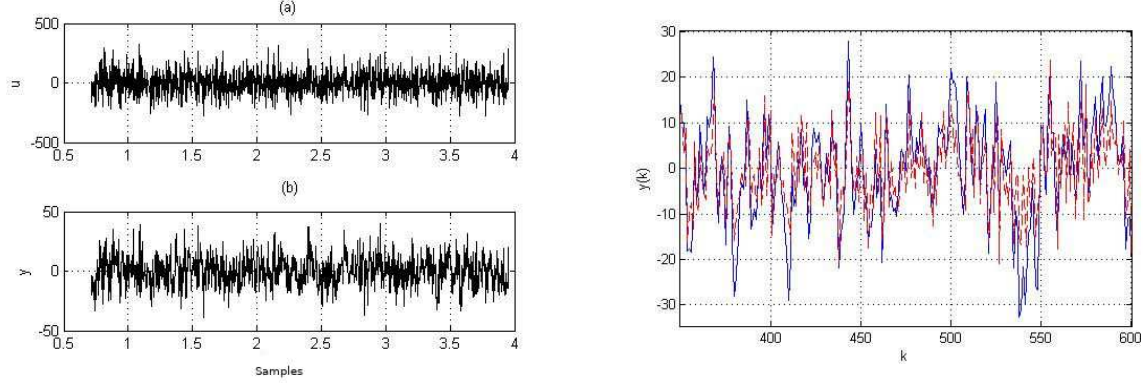


Fig. 4 Offline identification and validation evidence. (a) Phase-voltage input and phase-current output. (b) Free-run validation of the nonlinear surrogate (RMSE = 0.5860).

$$y(k) = \theta_1 u(k-1) + \theta_2 y(k-2) + \theta_3 u(k-2) + \theta_4 u(k-1)y(k-1), \quad (6)$$

with the nominal batch estimates

$$\hat{\theta}_0 = [0.0756 \ 0.2976 \ -0.0113 \ 0.0004]^T. \quad (7)$$

The nonlinear model achieved a validation RMSE of 0.5860, representing an approximately 22% reduction relative to the corresponding linear ARMAX model. More importantly for the present purpose, when fault-generated data were forced through the *same deterministic structure*, the coefficients changed markedly while the regressor set remained unchanged. This observation motivated the recursive detector.

4.4 Local pole/zero interpretation of coefficient drift

The relationship between the recursive coefficients and changes in the motor dynamics can be made explicit by linearizing Eq. (6) about an operating

point $(\bar{u}, \bar{y})$. For small perturbations around this operating point, let $u = \bar{u} + \delta u$ and $y = \bar{y} + \delta y$, yielding

$$\begin{aligned} \delta y(k) = & \theta_4 \bar{u} \delta y(k-1) + \theta_2 \delta y(k-2) \\ & + (\theta_1 + \theta_4 \bar{y}) \delta u(k-1) + \theta_3 \delta u(k-2). \end{aligned} \quad (8)$$

Hence, the local characteristic polynomial of the fixed NARX structure is

$$A(z^{-1}; \bar{u}, \theta) = 1 - \theta_4 \bar{u} z^{-1} - \theta_2 z^{-2}. \quad (9)$$

The corresponding local input-output transfer relation is therefore

$$G_{\text{loc}}(z; \bar{u}, \bar{y}) = \frac{\Delta Y(z)}{\Delta U(z)} = \frac{(\theta_1 + \theta_4 \bar{y})z^{-1} + \theta_3 z^{-2}}{1 - \theta_4 \bar{u} z^{-1} - \theta_2 z^{-2}}. \quad (10)$$

Equation (10) provides a structural interpretation of the four recursive coefficients. The coefficients θ_1 and θ_3 belong primarily to the numerator, i.e., the voltage-to-current input path, and therefore affect effective zeros and dynamic input coupling. The autoregressive coefficient θ_2 belongs to the

denominator and directly moves the effective local poles. The nonlinear cross coefficient θ_4 appears in both numerator and denominator through the operating point $(\bar{u}, \bar{y})$ and also participates in the static characteristic; it is therefore especially related to operating-point dependence. Recursive coefficient movement can thus be interpreted as movement of effective poles, zeros, and gain. Static-gain adaptation is used to absorb benign operating-point variation while preserving fault-induced dynamic changes. The four coefficients consequently form a compact diagnostic coordinate system rather than a high-fidelity simulation state.

4.5 Recursive parameter estimation

For online tracking, Eq. (6) is expressed as

$$y(k) = \psi^T(k)\theta(k) + e(k), \quad (11)$$

where

$$\psi(k) = \begin{bmatrix} u(k-1) \\ y(k-2) \\ u(k-2) \\ u(k-1)y(k-1) \end{bmatrix}. \quad (12)$$

A recursive least-squares estimator with forgetting factor λ updates the parameter vector according to:

$$\mathbf{K}(k) = \frac{\mathbf{P}(k-1)\psi(k)}{\lambda + \psi^T(k)\mathbf{P}(k-1)\psi(k)}, \quad (13)$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \mathbf{K}(k) \left[y(k) - \psi^T(k)\hat{\theta}(k-1) \right], \quad (14)$$

$$\mathbf{P}(k) = \frac{1}{\lambda} \left[\mathbf{P}(k-1) - \mathbf{K}(k)\psi^T(k)\mathbf{P}(k-1) \right]. \quad (15)$$

The experiments considered $\lambda = 0.9993$ and $\lambda = 1$. Values below 0.9993 increased parameter variance to a level that impaired discrimination between healthy and faulty operation. The recursive equations also make an implementation detail explicit: after the offline structure/initialization stage, the online recursion contains no dense matrix inversion. The covariance information is propagated from sample to sample through rank-one updates, and the only inverse operation in the RLS normalization is the reciprocal of the

scalar $d(k)$ in Eq. (1). This is one reason the four-parameter structure is particularly suitable for deterministic embedded execution.

4.6 Static-gain adaptation

A key feature of the polynomial representation is that its steady-state characteristic can be recovered analytically. At a fixed input $\bar{u}$ and output $\bar{y}$, Eq. (6) yields

$$\bar{y} = \frac{(\theta_1 + \theta_3)\bar{u}}{1 - \theta_2 - \theta_4\bar{u}}. \quad (16)$$

Using the recursively estimated coefficients, an online estimate $\hat{y}_s(k)$ of the static output is obtained. The operating-point correction is then represented by the gain

$$G_s(k) = \frac{\hat{y}_s(k)}{y(k)}. \quad (17)$$

This gain is fed back to the recursive model input. The purpose is not to create an additional fault index, but to prevent normal load-dependent gain changes from being incorrectly absorbed by the dynamic parameter vector. Section 5.5 demonstrates experimentally why this correction is essential.

5 Comparative Experimental Assessment

5.1 Incipient fault versus load variation

Figure 5 compares the recursive coefficient trajectories for the 1.5% ITSC with those produced by the 48.5% load-current change when $\lambda = 1$. The labels retained in the archived plots mark the event locations; the diagnostic information is the change of trajectory associated with each event, rather than the absolute coefficient value during estimator convergence. At the ITSC event, θ_1 and θ_2 exhibit clear upward discontinuities/trend changes and θ_3 exhibits a downward displacement. The load transition also perturbs θ_1 and, more strongly, the denominator-related θ_2 , because a change of operating point can move the effective poles. In contrast, the load-induced displacement of θ_3 is much smaller after static-gain adaptation. The cross coefficient θ_4 is weakly affected by

the ITSC but strongly reflects the load/operating-point transition. Thus, for the most incipient 1.5% condition, θ_3 provides the clearest single fault/load discriminator, while θ_2 supplies strong but less specific corroborating evidence.

The same signature becomes more pronounced for the 3% ITSC in Fig. 6. The fault produces a larger separation in θ_1 , a pronounced change in the pole-related coefficient θ_2 , and a marked displacement of θ_3 . Fault severity is therefore expressed mainly as a stronger excursion of the same dynamic coordinates rather than as a change in the selected model structure. Again, θ_2 is one of the most responsive coefficients but is not the most selective because the load transition also perturbs the denominator dynamics. The delayed-input numerator coefficient θ_3 retains the strongest fault-to-load contrast, whereas the weak ITSC response and marked operating-point dependence of θ_4 support its use as contextual/adaptation information rather than as a stand-alone fault indicator.

5.2 Diagnostic role and relative sensitivity of the NARX coefficients

The four recursive quantities should not be treated as equivalent alarms. Equation (10) separates their roles in the locally linearized voltage-to-current dynamics: θ_1 and θ_3 are predominantly numerator/input-path coefficients, θ_2 is an autoregressive denominator/output-feedback coefficient, and θ_4 couples input and output and affects both the dynamic denominator/numerator and the static gain through the operating point. This distinction explains the different sensitivities observed in Figs. 5 and 6.

For both fault severities, θ_1 , θ_2 , and θ_3 respond to the ITSC, but they are not equally selective. The pole-related coefficient θ_2 is highly sensitive because the fault changes the effective motor dynamics; however, a load-induced operating-point shift can also move the denominator dynamics. The coefficient θ_3 is clearly displaced by both 1.5% and 3% ITSCs while showing the smallest diagnostically relevant movement for the tested load transition, giving the best empirical fault/load selectivity in this motor. The coefficient θ_1 provides useful secondary evidence from the input-to-current numerator path. The nonlinear

cross coefficient θ_4 is comparatively insensitive to the ITSC and more responsive to operating-point change, which makes it more useful as contextual/adaptation information. Table 3 summarizes these roles. The ranking is specific to this identified four-term structure and is not intended as a universal ordering for arbitrary NARX models.

5.3 Effect of the forgetting factor

The forgetting factor defines a practical compromise between adaptation speed and estimator variance. With $\lambda = 0.9993$, recent samples are assigned greater relative weight, allowing the estimator to respond more rapidly to dynamic changes, but at the expense of noisier parameter trajectories. In contrast, with $\lambda = 1$, the parameter variance is reduced, and the separation between operating conditions becomes clearer, although this comes at the cost of a slower response to changes. For the 3% fault, the observed delay was approximately 1.2s, which is acceptable for the seeded incipient-fault severity considered here. These results suggest that λ should be treated as a diagnostic design parameter rather than selected solely from generic recursive-identification recommendations.

5.4 Distribution-level separation

The statistical analysis used 2000 recursive parameter estimates per condition. Figure 7 focuses on θ_3 , the coefficient that showed the best compromise between fault sensitivity and load robustness. The healthy and 1.5% fault distributions have only limited overlap, while the 3% fault distributions are clearly separated. By contrast, the shift caused by the load change remains comparatively small. This distribution-level view complements the time-domain trajectories and reduces dependence on a single realization.

5.5 Ablation: why static-gain adaptation matters

To isolate the contribution of the auxiliary static characteristic, the same NARX structure was recursively estimated without the gain correction of Eq. (17). Figure 8 summarizes the resulting parameter trajectories. Without gain adaptation, the recursive algorithm becomes effectively insensitive to the 1.5% fault and the 3% fault becomes

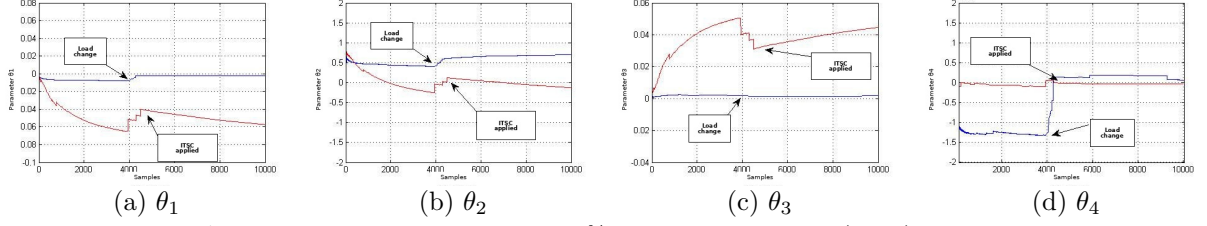


Fig. 5 Recursive NARX coefficient trajectories for the 1.5% ITSC and load change ($\lambda = 1$).

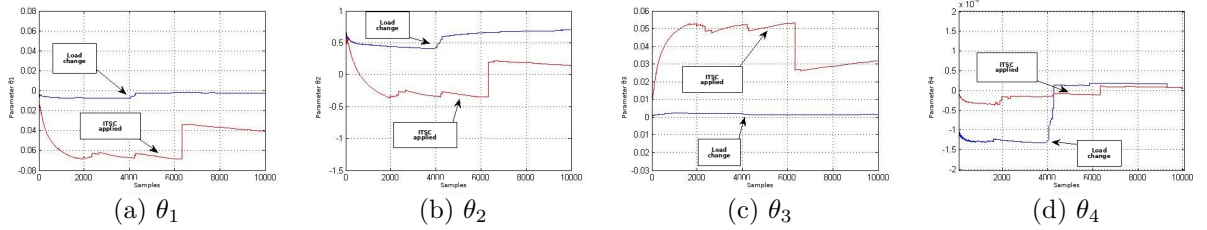


Fig. 6 Recursive NARX coefficient trajectories for the 3% ITSC and load change ($\lambda = 1$).

difficult to distinguish from the load transition. This experiment is important because it shows that the diagnostic performance is not explained merely by adding polynomial terms: the improvement arises from combining the nonlinear structure with operating-point adaptation.

5.6 Faulted phase versus unaffected phases

When the voltage and current from the faulted phase are used, the recursive parameters show a clear difference between fault and load change. When the same estimator is applied to either unaffected phase, the distinction becomes substantially weaker for both fault severities. The practical implication is that a deployment cannot assume knowledge of the faulted phase in advance; all three phase pairs should be monitored in parallel, and a phase-wise decision layer should identify the channel with the strongest parameter deviation.

6 Discussion

The results reinforce the distinction between a *simulation model* and a *diagnostic model*. The white-box dq model supplies physically consistent healthy dynamics, whereas the identified NARX surrogate is intentionally reduced. Its free-run accuracy must be adequate, but its diagnostic role is to provide a fixed low-order coordinate

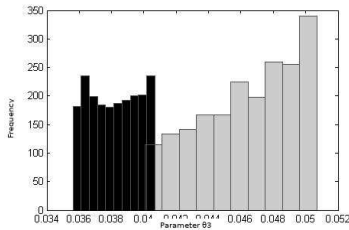
system in which dynamic changes appear as coefficient drift; Eq. (10) links that drift to effective pole, zero, and gain movement. Nonlinearity alone is not sufficient: the ablation study shows that static-gain adaptation is decisive for fault/load discrimination, while the forgetting factor controls the responsiveness–variance trade-off.

The coefficient roles also suggest an embedded decision logic. The delayed-input numerator coefficient θ_3 is the preferred primary fault coordinate because it exhibited the highest selectivity against the tested load transition. The numerator coefficient θ_1 provides secondary evidence, whereas the denominator coefficient θ_2 is highly sensitive to pole movement but less specific because normal operating-point changes can also perturb the denominator. The cross coefficient θ_4 is better interpreted as operating-point/context information supporting gain adaptation. A practical rule can therefore require a fault-consistent θ_3 excursion corroborated by θ_1 and/or θ_2 , while using θ_4 and the gain correction to reject benign load changes.

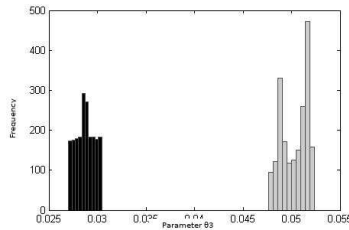
This operating-point rejection is industrially important because load variability is normal field behavior [18]. Relative to high-capacity machine-learning and digital-twin approaches [1, 6, 14, 15, 19], the proposed method requires no labeled multi-severity training set and retains only four dynamic coefficients per phase. Neural and fuzzy systems are embeddable [4, 17];

Table 3 Structural role and qualitative diagnostic sensitivity of the recursive NARX coefficients.

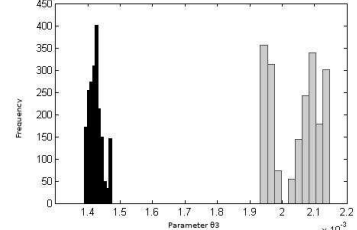
Coeff.	Local dynamic role	1.5% ITSC	3% ITSC	Load-change sensitivity	Recommended role	diagnostic
θ_1	Numerator/input path, $u(k-1)$; effective zeros/gain	Clear; medium-high	Clearer; high	Low-moderate after gain adaptation	Secondary fault indicator; corroborates θ_3	indicator;
θ_2	Denominator/output feedback, $y(k-2)$; directly moves effective poles	Pronounced; high	Pronounced; high	Moderate-high	Very sensitive but less specific; corroborating pole-shift indicator	
θ_3	Delayed numerator/input path, $u(k-2)$; effective zeros/dynamic coupling	Clear; high	Clear; high	Low	Primary fault discriminator in these experiments; best fault/load contrast	
θ_4	Nonlinear $u(k-1)y(k-1)$ cross term; operating-point dependent	Weak; low	Weak; low	High/context dependent	Operating-point/adaptation indicator; not a stand-alone ITSC alarm	



(a) Healthy vs. 1.5% ITSC



(b) Healthy vs. 3% ITSC



(c) Two load levels

Fig. 7 Empirical distributions of θ_3 for fault and load-change experiments ($\lambda = 1$), based on 2000 recursive estimates per condition.

the defensible advantage here is structural simplicity: no windowed FFT/DWT, learned-network inference, or repeated matrix inversion, only fixed-dimension matrix-vector/rank-one operations and scalar normalization.

The measured 1.2s delay is evidence-accumulation latency rather than processor latency: at 1kHz, the arithmetic update occurs every millisecond, but the alarm emerges only after the parameter trajectory separates from normal variability. This addresses an earlier degradation stage than conventional protection, because an incipient ITSC can produce only a small terminal-current change while local circulating current and insulation damage are already developing [3, 5]. Conventional protection remains indispensable once a fault develops into a severe condition. The experiments nevertheless used one grid-fed laboratory motor, seeded ITSCs, and one load transition; target-hardware timing, inverter-fed operation, supply disturbances, additional

fault classes, and event-level false-alarm metrics remain to be validated.

7 Conclusions

A recursive model-based strategy was assessed for discriminating incipient stator inter-turn short circuits from normal load variation in a three-phase induction motor. A physics-based symmetric dq model generated persistently exciting healthy data, from which a deliberately low-order polynomial NARX surrogate was selected. The surrogate was not designed as a high-fidelity simulator; its fixed structure was used so that small changes in the motor dynamics appear as coefficient—and therefore effective pole/zero—movement. Static-gain adaptation was essential: without it, sensitivity to the 1.5% ITSC was lost and discrimination of the 3% ITSC was reduced.

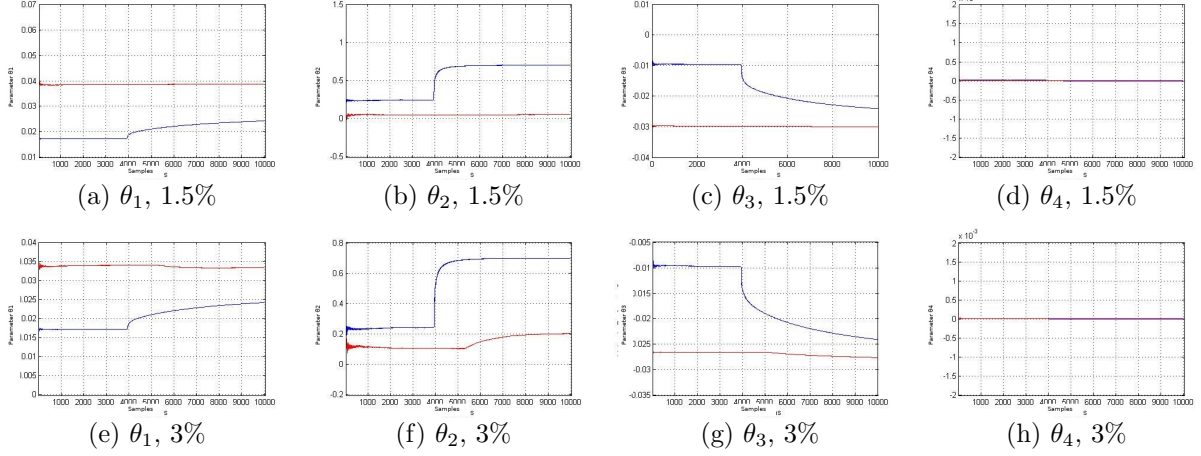


Fig. 8 Ablation test without static-gain adaptation ($\lambda = 1$) for 1.5% and 3% ITSC under load variation, showing the loss of discriminative behavior.

Across seven repeated tests per condition, the fault-induced coefficient changes remained distinguishable from the 48.5% load-current variation. The delayed-input coefficient θ_3 provided the clearest fault/load selectivity and is the preferred primary diagnostic coordinate; θ_1 is a useful secondary numerator-path indicator; θ_2 is highly sensitive but less specific because operating-point changes also perturb the denominator, and θ_4 is better suited to operating-point/adaptation context. The online estimator updates only four coefficients and a 4×4 covariance matrix, requires no matrix inversion, and runs sample by sample at the experimental 1-kHz rate. The approximately 1.2-s response is therefore best interpreted as evidence-accumulation latency, supporting the method as a candidate for embedded retrofit condition monitoring. Future work should benchmark execution time and memory on target hardware and validate the strategy under inverter-fed operation and additional operating/fault conditions.

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Use of generative AI. ChatGPT (OpenAI) assisted literature organization, language editing, restructuring, and explanatory text/tables. All scientific content was checked against archived study records and cited sources; the authors retain full responsibility.

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