

FAULT ANALYSIS AND PREDICTIVE MAINTENANCE SIMULATION AND ANALYSIS OF INDUCTION MOTOR PID CONTROL SYSTEMS

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ABSTRACT

In closed-loop induction motor drives, conventional PID regulators inherently mask early-stage machine degradation by continuously compensating for output tracking errors. This paper evaluates these limitations through a multi-signal simulation model implemented in MATLAB/Simulink, titled "Fault Analysis and Predictive Maintenance Simulation and Analysis of Induction Motor PID Control Systems." Utilizing dual parallel branches with identical PID gains ($K_p = 5.23$, $K_i = 12.45$, $K_d = 0.08$), a 5.5 kW motor is subjected to a cascading fault sequence: an electrical Inter-Turn Short Circuit (1.5–2.5 s), a structural Phase Loss (2.5–3.5 s), and a mechanical Overload (3.5–5.0 s).

The results demonstrate that while the PID loop maintains average velocity tracking at 150 rad/s, it fails to mitigate severe high-frequency torque ripples and stator overcurrent's. Following phase loss and overload injection, the RMS stator current escalates to 10.5 A and 12.3 A, respectively, breaching the machine's 11 A rated safety threshold. To address this masking effect, a multi-parameter diagnostic vector fusing speed errors, torque pulsations, RMS currents, and Total Harmonic Distortion is mapped into a unified Predictive Maintenance Health Index. This indicator transforms complex operational distress into distinct, stepped transitions (surging from 0.95 to 7.85) that successfully breach Warning and Critical thresholds in real time, validating the framework as a reliable prognostic tool for industrial asset monitoring.

Keywords: *Induction Motor, PID Control, Fault Analysis, Predictive Maintenance, Health Index.*

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I. INTRODUCTION

Three-phase induction motors serve as the primary workhorses of modern industrial infrastructure, driving critical applications across manufacturing, automation, chemical processing, and electric propulsion systems. Due to their rugged design, cost-effectiveness, and reliable operational characteristics, these machines are frequently subjected to harsh operating environments, cyclic thermal stresses, and unexpected mechanical transients. Prolonged exposure to such demanding conditions inevitably precipitates structural degradation, leading to electrical and mechanical faults. If left undetected, minor localized anomalies can rapidly cascade into

catastrophic component failures, resulting in extensive unscheduled downtime, severe financial losses, and compromised personnel safety. Consequently, developing robust, real-time condition-monitoring frameworks has become a paramount priority for contemporary industrial asset management. Historically, industrial maintenance paradigms have transitioned from reactive "run-to-failure" strategies to time-based preventive routines. While preventive approaches reduce unexpected breakdowns, they frequently incur unnecessary labor costs and premature component replacements. To overcome these inefficiencies, modern industrial frameworks are increasingly adopting predictive maintenance (PdM). Predictive maintenance utilizes continuous data-acquisition and signal-processing techniques to track real-time machine health indices, allowing for the precise prognosis of impending abnormalities before failure thresholds are breached. However, implementing an effective PdM chain for induction motor drives introduces significant complexities, particularly when the machine operates within a closed-loop control system. In industrial applications, induction motors are rarely operated in open-loop configurations; instead, they are governed by feedback regulators such as conventional Proportional-Integral-Derivative (PID) controllers to maintain precise speed tracking. Closed-loop control drastically alters the manifestation of internal faults. Because the PID loop continuously adjusts the stator frequency and voltage commands to compensate for speed deviations, it inherently masks the immediate visual indicators of early-stage degradation. For instance, a localized winding fault or an emergent load imbalance that would normally cause a visible drop in open-loop speed is instantly counteracted by the controller's integral action. This control compensation cloaks the anomaly, while shifting the stress directly into other diagnostic variables, such as electromagnetic torque ripples and stator current signatures. Therefore, relying on a single diagnostic parameter, such as rotor velocity alone, is fundamentally inadequate for reliable closed-loop fault diagnosis.

To address these challenges, this paper presents a comprehensive, multi-parameter simulation and monitoring framework developed within the MATLAB/Simulink environment, titled Fault Analysis and Predictive Maintenance Simulation and Analysis of Induction Motor PID Control Systems. The proposed architecture establishes a parallel evaluation framework comprising an identical healthy reference path and a fault-scheduled path utilizing a unified set of PID tuning gains ($K_p = 5.23$, $K_i = 12.45$, $K_d = 0.08$). By subjecting both models to an identical step command of 150 rad/s across a 5.0 s window, this study systematically unmask how classical feedback loops interact with a cascading fault profile. The investigated fault sequence models three major categories of industrial distress: an electrical Inter-Turn Short Circuit (ITSC) fault ($1.5 \leq t < 2.5$ s), a severe structural Phase Loss fault ($2.5 \leq t < 3.5$ s), and a mechanical Overload condition ($3.5 \leq t \leq 5.0$ s). By extracting and synthesizing co-dependent diagnostic features—namely rotor speed tracking deviations, electromagnetic torque pulsations, Root-Mean-Square (RMS) stator current variations, and Total Harmonic Distortion (THD) the framework constructs a unified Predictive Maintenance Health Index. This health index continuously maps the machine's operational degradation across distinct Healthy, Warning, and Critical thresholds, providing a complete, closed-loop model-based diagnostic and prognostic chain.

II. Literature Review

The field of induction motor condition monitoring and fault diagnosis has been extensively documented, evolving alongside advancements in digital signal processing, sensor technologies, and mathematical modeling techniques. Researchers have classified induction motor anomalies into distinct categories based on their physical origins: electrical stator faults, rotor winding disruptions, bearing degradations, and external mechanical eccentricities or overloads. Among these, stator-related faults particularly Inter-Turn Short Circuits (ITSC) are widely recognized as some of the most destructive and fast-acting anomalies. An ITSC initiates due to localized thermal degradation, chemical attack, or voltage surges that break down the dielectric insulation between adjacent wire turns within a single-phase winding. Authors in have demonstrated that while an ITSC initially alters only a fraction of the phase turns, the resulting circulating currents inside the shorted loop generate localized hot spots that rapidly accelerate insulation melting, quickly causing catastrophic phase-to-phase or phase-to-ground faults. Another critical electrical anomaly frequently encountered in industrial drive networks is the open-circuit single-phase loss, often caused by a blown fuse, contactor failure, or physical cable disconnection. In open-loop configurations, a phase loss prevents the motor from starting or causes it to stall under heavy loads. However, under closed-loop velocity regulation, the machine continues to operate by drawing unbalanced power through the remaining healthy phases. Literatures focusing on asymmetrical machine operations under phase-loss conditions emphasize that the missing phase forces the stator to generate a highly distorted, non-axisymmetric space vector magnetomotive force (MMF). This asymmetry decomposes into forward and backward rotating magnetic fields, which severely compromises the efficiency of electromagnetic torque production. To detect these electrical deviations, Motor Current Signature Analysis (MCSA) has emerged as the industry-standard, non-invasive condition-monitoring technique. MCSA operates on the principle that any structural, electrical, or mechanical asymmetry within the motor modulates the air-gap flux density, which in turn imprints unique fault-related frequency harmonics onto the stator current waveform. For instance, ITSC faults are classically identified by tracking specific sideband frequencies defined by:

$$f_{ITSC} = f_s \left(\frac{1 \mp s}{P} \right)$$

where f_s is the supply frequency, s is the rotor slip, and P is the number of pole pairs. Similarly, open-circuit phase losses and mechanical overloads significantly increase the fundamental Root-Mean-Square (RMS) current value and introduce severe harmonic distortions, making Total Harmonic Distortion (THD) an invaluable scalar metric for aggregate fault tracking.

Despite the high sensitivity of MCSA and torque ripple analysis in open-loop operations, their diagnostic accuracy degrades when integrated into closed-loop controlled drive systems, such as those governed by conventional PID regulators. In field-oriented control (FOC) or direct torque control (DTC) loops, the primary function of the feedback regulator is to suppress any deviations from the reference trajectory. As established by researchers in the field, if a torque ripple or speed dip occurs due to an internal fault, the PID controller immediately adjusts the voltage commands to cancel out the error. This regulatory feedback mechanism effectively "shuffles" the fault signatures from the output variables (speed) back into the input control signals and across the internal state variables (current and torque envelopes). Consequently, classical single-signal

diagnostic methods often yield false negatives or fail to accurately quantify fault severity in closed-loop systems. To overcome the masking effects inherent to feedback loops, modern research has shifted toward multi-signal condition monitoring and multi-parameter data fusion architectures. By continuously assessing a combination of mechanical variables (rotor speed deviations, electromagnetic torque ripples) and electrical variables (RMS stator currents, THD indicators), researchers can establish decoupled, highly accurate diagnostic vectors that remain unmasked by controller compensation. Furthermore, state-of-the-art predictive maintenance paradigms require translating these multi-parameter diagnostic vectors into a simplified, continuous scalar known as a Health Index (HI). A properly formulated health index quantifies machine degradation linearly or quadratically, mapping it against discrete, actionable alert thresholds (such as Warning and Critical levels). This allows industrial operators to schedule targeted maintenance actions well in advance of a total system failure.

While numerous studies have proposed advanced, non-linear controllers like Sliding Mode Control (SMC) or Fuzzy Logic Control (FLC) to enhance fault-tolerant drive performance, a comprehensive evaluation of how a baseline, conventional linear PID controller responds to multiple, cascading electrical and mechanical faults remains critically essential. Understanding the clear limits of classical linear control loops in handling fault-induced asymmetries is vital for establishing baseline diagnostic metrics. This paper fills this analytical gap through the study of Fault Analysis and Predictive Maintenance Simulation and Analysis of Induction Motor PID Control Systems, providing a model-based, multi-signal predictive maintenance chain that systematically maps speed, torque, current, and THD deviations under a sequential fault schedule into a real-time health indicator.

III. EXPERIMENTAL AND METHODOLOGY

Figure 1 illustrates the overall architecture of the proposed MATLAB/Simulink framework developed for the fault analysis and predictive maintenance of an induction motor under conventional PID control. The framework is designed to evaluate and compare motor behavior under healthy and faulty operating conditions while maintaining identical PID controller parameters in both cases. The simulation begins with a reference speed of 150 rad/s, which is simultaneously supplied to the healthy and faulty control branches. In each branch, a conventional PID controller processes the difference between the reference speed and the measured motor speed and generates the corresponding frequency command for the induction motor model. The use of the same PID gains in both branches provides a consistent basis for investigating the effect of faults on the closed-loop motor response. The healthy path represents the nominal operating condition of the induction motor without fault injection. In contrast, the fault path incorporates a fault-scheduling mechanism that introduces different operating abnormalities during the simulation period. The considered fault sequence consists of an inter-turn short circuit (ITSC) from 1.5 to 2.5 s, phase loss from 2.5 to 3.5 s, and mechanical overload from 3.5 to 5.0 s. The fault-scheduling block generates the corresponding load torque, fault type, and fault severity signals, which are supplied to the faulty motor model. For both operating paths, the induction-motor models provide four principal diagnostic variables: rotor speed, electromagnetic torque, stator current, and THD. These signals are recorded through the data-acquisition and monitoring blocks and are

subsequently used for comparative performance assessment. Speed deviation provides information regarding the tracking capability of the PID controller, while current and torque variations provide indicators of changes in the electrical and mechanical operating conditions. Current-based spectral characteristics and THD are also commonly used in induction-motor condition monitoring and fault diagnosis. The resulting measurements are supplied to the Fault Diagnostic stage, where several indicators are evaluated, including speed error, RMS current, THD, fault severity, and the proposed health index. These indicators provide a multi-parameter representation of the motor's operating condition rather than relying on a single measurement. Such multi-signal condition-monitoring approaches are consistent with current research trends in induction-motor fault diagnosis and predictive maintenance.

Finally, the diagnostic information is processed by the Predictive Maintenance Assessment stage, which provides an overall indication of the motor's condition. The assessment is represented using three operating states: Healthy, Warning, and Critical. The resulting framework therefore establishes a complete monitoring chain from closed-loop speed control and fault injection to condition monitoring, fault diagnosis, and maintenance-oriented assessment. Overall, the proposed architecture provides a simulation environment for investigating how different electrical and mechanical faults influence the dynamic behavior of a PID-controlled induction motor and for evaluating diagnostic indicators that can support condition-based and predictive maintenance strategies. The framework is model-based and simulation-oriented; therefore, the diagnostic THD indicator should be distinguished from experimentally measured FFT-based THD unless an actual three-phase current spectrum is incorporated into the model.

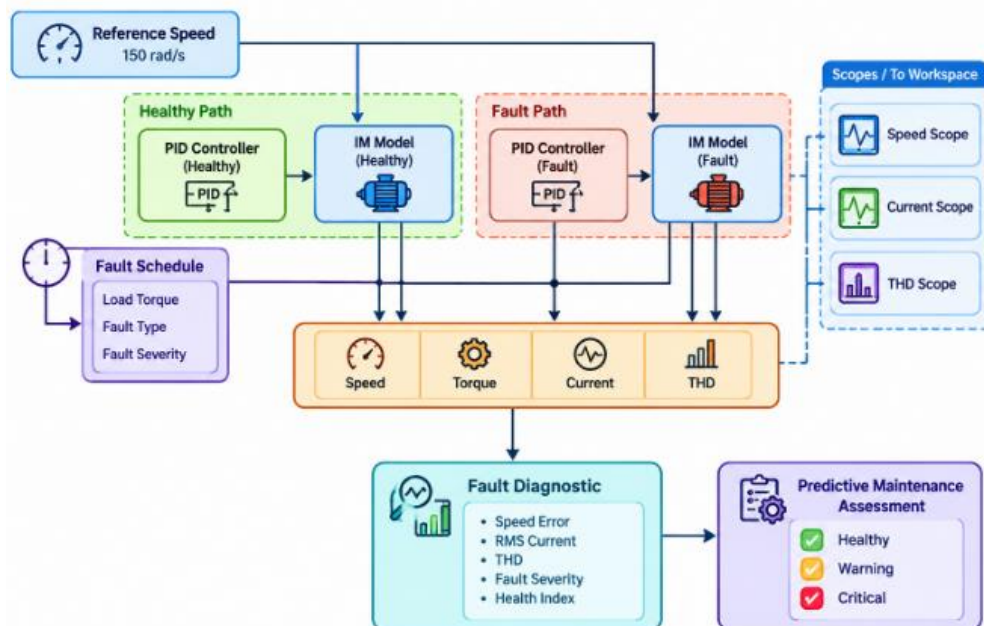


Figure 1: Proposed PID-Based Induction Motor Fault Diagnosis and Predictive Maintenance Framework.

The proposed methodology is developed in MATLAB/Simulink to investigate the dynamic behavior of a three-phase induction motor under healthy and faulty operating conditions and to evaluate the applicability of a conventional proportional integral derivative (PID) controller for speed regulation and condition monitoring. The proposed framework consists of two parallel simulation paths: a healthy operating path and a faulty operating path, as illustrated in Fig. 1. Both paths employ the same reference speed and PID controller parameters, allowing the effects of fault conditions to be evaluated without introducing changes in the control algorithm. The reference speed is set to 150 rad/s, while the simulation is performed using a discrete sampling time of 10^{-4} s over a total simulation period of 5 s. The faulty operating path incorporates three predefined fault conditions: inter-turn short circuit (ITSC), phase loss, and mechanical overload. The resulting motor variables are continuously monitored and subsequently used to derive diagnostic indicators for condition assessment and predictive-maintenance decision-making.

• PID Controller

A conventional PID controller is employed to regulate the induction-motor speed. The controller receives the difference between the reference speed and the measured motor speed as its input. The speed error is defined as

$$e(t) = \omega_{ref}(t) - \omega_m(t)$$

Where: $e(t)$ represents the speed error, ω_{ref} is the reference angular speed, and ω_m is the measured motor speed. The continuous PID control law can be expressed as

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}$$

where K_p , K_i , and K_d denote the proportional, integral, and derivative gains, respectively.

In the proposed model, the PID gains are selected as

$$D(k) = \frac{e(k) - e(k-1)}{T_s}$$

The resulting control signal is used to generate the motor frequency command. Frequency limits are incorporated into the controller to maintain the commanded frequency within the predefined operating range. An integral limitation is also included to reduce the effect of excessive integral accumulation and improve the numerical stability of the controller.

• Induction Motor Model

The induction motor is represented using a simplified dynamic model formulated in the rotating dq -reference frame. This approach enables the principal electrical and mechanical dynamics of the motor to be represented using a computationally efficient model suitable for MATLAB/Simulink simulation. The electrical parameters used in the model are summarized as follows:

Table 1: The electrical parameters used in the model.

Parameter	Value
Rated power	5.5 kW
Number of poles	4
Supply frequency	50 Hz
Stator resistance R_s	1.35 Ω
Rotor resistance R_r	1.18 Ω
Stator leakage inductance L_{ls}	0.0065 H
Rotor leakage inductance L_{lrL}	0.0065 H
Magnetizing inductance L_m	0.145 H
Stator inductance L_s	0.1515 H
Rotor inductance L_r	0.1515 H
Moment of inertia J	0.024 kg·m ²
Viscous friction coefficient B	0.0012 N·m·s/rad
Pole pairs P	2

The stator and rotor currents are calculated from the corresponding flux linkages. For example, the dd-axis stator and rotor currents can be represented as

$$i_{qr} = \frac{-L_m \psi_{qs} + L_s \psi_{qr}}{L_s L_r - L_m^2}.$$

The stator and rotor flux dynamics are then calculated from the corresponding voltage equations. The electromagnetic torque is determined from the dq -axis flux and current components as. The mechanical dynamics of the motor are represented by

$$J \frac{d\omega_m}{dt} = T_e - T_L - B\omega_m$$

Where: T_e is the electromagnetic torque, T_L is the applied load torque, J is the rotor inertia, and B is the viscous friction coefficient. The motor model therefore provides the principal outputs required for subsequent analysis, including:

- motor speed,
- electromagnetic torque,
- stator current, and
- a THD-related diagnostic indicator.

The reference operating speed used in the simulation is

$$\omega_{ref} = 150 \text{ rad/s.}$$

This corresponds approximately to 1432 rpm.

• Fault Modeling

To investigate the response of the induction motor to abnormal operating conditions, a dedicated Fault Schedule subsystem is incorporated into the faulty simulation path. The fault schedule generates three principal signals:

1. Load torque,
2. Fault type, and
3. Fault severity.

Table 2: proposed simulation considers four sequential operating states:

Time interval	Operating condition	Load torque	Fault type	Severity
0–1.5 s	Healthy	8 N·m	None	0
1.5–2.5 s	ITSC	9 N·m	Inter-turn short circuit	0.35
2.5–3.5 s	Phase loss	10 N·m	Phase loss	0.70
3.5–5.0 s	Mechanical overload	12 N·m	Overload	1.00

The fault type and severity signals are separated using a demultiplexer and supplied to the induction-motor model. This structure allows the model to reproduce a sequence of different operating conditions during a single simulation run.

• Condition Monitoring

The condition-monitoring stage evaluates the motor response using the variables generated by the induction-motor model. The principal monitored variables are speed, electromagnetic torque, stator current, and THD-related information.

The measured speed is compared with the reference speed to determine the speed-tracking error:

$$e_{\omega}(t) = \omega_{ref}(t) - \omega_m(t).$$

The RMS value of the stator current is calculated to provide an additional indication of changes in the electrical operating condition:

$$I_{RMS} = \sqrt{\frac{1}{N} \sum_{k=1}^N i^2(k)}.$$

Changes in current magnitude can provide useful information concerning increased loading and abnormal motor operation. Similarly, deviations in electromagnetic torque and motor speed can indicate deterioration in the motor's ability to maintain the commanded operating point. The framework also includes a THD-related diagnostic signal. In the current implementation, this signal is generated as a model-based diagnostic indicator associated with the imposed fault conditions, rather than being calculated from an FFT of measured three-phase abc currents. Consequently, the THD values generated by the present model should be interpreted as simulation-based indicators rather than experimentally measured harmonic distortion. The collected healthy and faulty signals are stored using the To Workspace blocks, enabling subsequent numerical analysis in MATLAB. Scope blocks are also employed to provide direct visualization of the transient response. The condition-monitoring stage therefore provides a set of indicators that can be summarized as

$$\mathbf{X} = [e_{\omega}, I_{RMS}, T_e, THD, S_f]$$

Where: S_f represents the assigned fault-severity level.

• Predictive Maintenance Assessment

The final stage of the proposed framework converts the monitored motor variables into an overall assessment of the motor operating condition. The objective is to establish a quantitative basis for distinguishing between normal operation and progressively deteriorating conditions.

The assessment considers changes in:

- speed-tracking performance,
- RMS stator current,
- electromagnetic torque,
- THD-related diagnostic response, and
- predefined fault severity.

A normalized health index can be formulated conceptually as

$$HI=1-D$$

Where: D represents the normalized degradation level. Under normal operating conditions, the degradation level is expected to remain low and the corresponding health index remains close to its nominal value. As abnormal conditions become more severe, the diagnostic indicators change and the health index decreases. For practical interpretation, the resulting condition can be categorized into three states:

- Healthy: The motor operates close to its nominal condition, with relatively small speed error and normal current and torque behavior.
- Warning: The monitoring indicators show a noticeable deviation from the healthy baseline, suggesting that the motor condition requires increased monitoring.
- Critical: The monitored variables exhibit substantial deterioration or a severe fault condition is detected, indicating that maintenance intervention should be considered.

• MATLAB Simulink

Figure 2 illustrates the proposed MATLAB/Simulink framework developed for the analysis of induction-motor performance under healthy and faulty operating conditions using a conventional PID speed controller. The proposed model consists of two parallel closed-loop simulation paths, namely the healthy motor path and the faulty motor path, which operate under the same reference speed and PID control strategy. This parallel structure enables a direct comparison between the nominal motor response and its behavior under different fault conditions. The simulation begins with a constant reference speed of 150 rad/s, which is simultaneously supplied to the healthy and faulty PID controllers. The PID controllers generate the corresponding frequency command, f_{cmd} , required to regulate the motor speed. The same controller parameters are maintained for both operating paths in order to ensure that the observed differences in motor behavior are primarily associated with the imposed operating conditions and faults rather than changes in the control algorithm. For the healthy operating condition, the Healthy Schedule block provides the nominal load torque and zero fault condition to the induction-motor model. The corresponding PID controller receives the measured motor speed through a Unit Delay block. The delay is incorporated into the feedback loop to avoid direct algebraic dependency and to represent the discrete-time implementation of the control system. In parallel, the Fault Schedule block defines the fault scenario applied to the faulty motor. The schedule generates three principal parameters: load torque, fault type, and fault severity. These signals are separated using the corresponding Demux block and supplied to the faulty induction-motor model. In the implemented simulation, the fault conditions are introduced sequentially over predefined time intervals, including inter-turn short circuit (ITSC), phase loss, and mechanical overload. Consequently, the model enables the dynamic response of the induction motor to be evaluated before, during, and after the occurrence of each

fault. Both motor models are represented by the IM_DQ_Model, which implements a simplified dynamic representation of the induction motor in the rotating dq -reference frame. The model receives the commanded frequency, load torque, and fault condition and calculates the principal electrical and mechanical variables. The main outputs include rotor speed, electromagnetic torque, stator current, and THD-related diagnostic information.

The output signals from both the healthy and faulty motor paths are simultaneously recorded using To Workspace blocks. The recorded data are subsequently used for quantitative performance and condition-monitoring analysis. In addition, the Scope blocks provide real-time visualization of the speed, current, and THD responses, allowing the transient effects associated with the different operating conditions to be observed directly. The resulting architecture establishes a complete simulation chain from speed reference and closed-loop PID control to fault injection, motor dynamic response, signal acquisition, and condition assessment. By maintaining the same PID controller structure in both paths, the framework provides a consistent basis for comparing healthy and faulty motor responses. This comparison can subsequently be used to extract diagnostic indicators such as speed deviation, RMS stator current, THD, fault severity, and health index, which form the basis for the proposed predictive-maintenance assessment

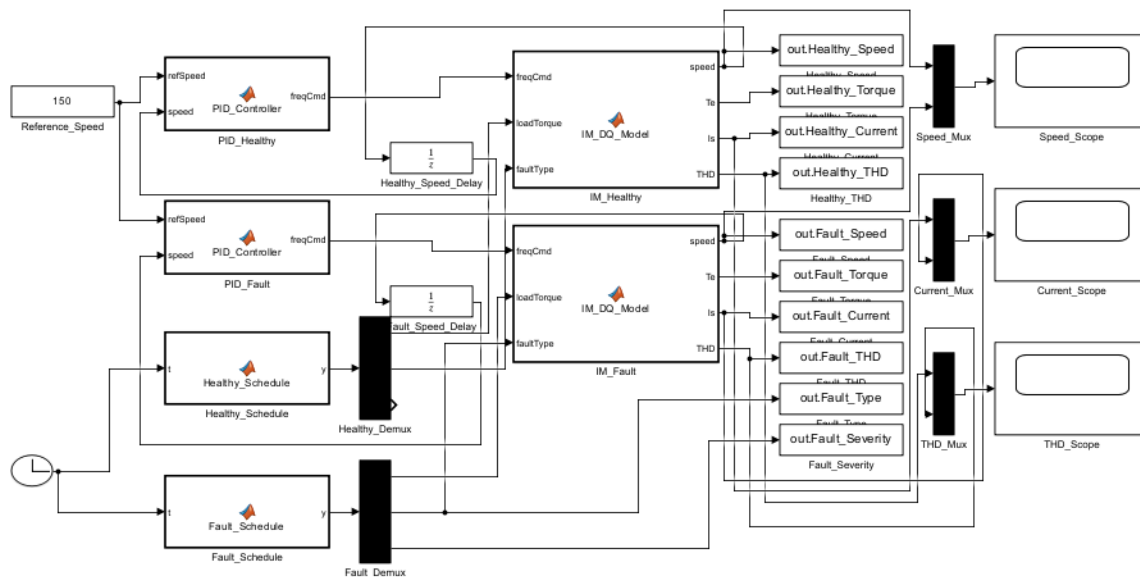


Figure 2. MATLAB/Simulink Framework for PID-Based Induction Motor Fault Analysis and Predictive Maintenance.

The dynamic speed tracking performance of the induction motor under the conventional PID control framework is presented in Figure 3, evaluated against a step command vector of 150 rad/s. During the initial startup interval ($0 < t < 0.3$ s), the system exhibits highly aggressive transient dynamics, culminating in a significant peak overshoot of 169 rad/s at approximately 0.3 seconds before the error attenuation loop gradually guides the velocity trajectory toward the steady-state threshold. Prior to fault injection, the healthy operation window reveals sustained high-frequency speed ripples, primarily driven by core torque pulsations and inherent inverter switching frequencies. The introduction of an Inter-Turn Short Circuit (ITSC) fault at 1.5 seconds induces a

severe electrical asymmetry within the stator windings; while the proportional-integral-derivative actions effectively clamp the average rotor velocity to the target baseline, the controller proves incapable of dampening the amplified, high-amplitude speed oscillations. Furthermore, the application of an open-circuit Phase Loss anomaly at 2.5 seconds triggers an instantaneous drop in electromagnetic torque, manifested as a sharp downward velocity dip. Although the conventional PID loop demonstrates robust recovery characteristics by restoring the mean operational speed to 150 rad/s within a transient window of 0.05 seconds, the persistent, heavy speed ripples highlight the critical limitations of classical linear control topologies in decoupled disturbance rejection during severe asymmetrical stator faults.

The dynamic response of the electromagnetic torque under the conventional PID control framework is presented in Figure 4, evaluating both the healthy and faulty machine profiles over a 5.0-second simulation window. During the initial transient startup phase ($0 \leq t < 0.5$ s), the system exhibits aggressive electromagnetic pulsations, with peak torque values fluctuating sharply between a maximum of 60 Nm and a minimum of -20 N.m. This violent oscillation is indicative of high inrush starting currents before the controller guides the system into steady-state operation, stabilizing at an average torque baseline of approximately 8 Nm with inherent high-frequency torque ripples. The sequential injection of faults systematically destabilizes the balanced structural dynamics of the drive system:

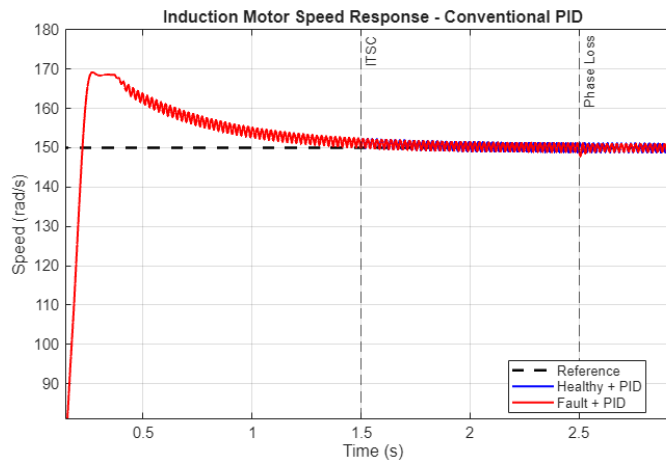


Figure 3: The induction motor speed response.

- Inter-Turn Short Circuit (ITSC) Fault ($t = 1.5$ s): The introduction of the winding short circuit causes an immediate expansion in the torque ripple envelope, visualized by the divergence between the healthy state (blue baseline) and the faulty operating profile (red envelope).
- Phase Loss Anomaly ($t = 2.5$ s): The abrupt open-circuit phase detachment induces a sudden transient torque spike peaking at approximately 23 N.m. While the PID controller forces the average torque back to its operational baseline, the sustained asymmetric magnetic field prevents any mitigation of the wide steady-state ripple bands.

- Overload Profiling ($t = 3.5$ s): Upon the introduction of the overload condition, a prominent vertical shifting of the torque boundaries is observed. The lower limit of the faulty torque envelope exhibits a distinct separation from the healthy baseline, demonstrating a profound degradation in core magnetic flux symmetry.

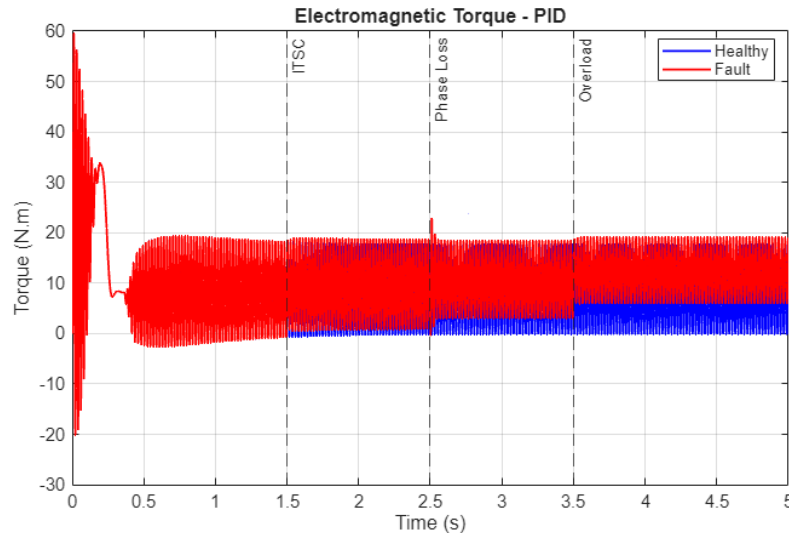


Figure 4: The dynamic response of the electromagnetic torque.

The transient and steady-state profile of the root-mean-square (RMS) stator current under both healthy and faulty operating conditions is illustrated in Figure 5. During the initial startup phase ($0 \leq t < 0.5$ s), the system experiences a massive inrush current characteristic of induction motor induction, peaking at approximately 47 A. As the motor accelerates and approaches its steady-state reference speed, the RMS current drops sharply to a nominal no-load/light-load value of approximately 9 A, which is safely below the motor's Rated Current threshold of 11 A (indicated by the horizontal dashed line). The sequential fault and load profiling dynamically impact the current consumption as follows:

- Inter-Turn Short Circuit (ITSC) Fault ($t = 1.5$ s): Following the injection of the winding short circuit, a minor upward shift is registered in the faulty profile (red curve) compared to the healthy baseline (blue curve). This minor escalation reflects the reduction in effective phase impedance due to the shorted turns, prompting a slight rise in current draw up to roughly 9.5 A.
- Phase Loss Anomaly ($t = 2.5$ s): The occurrence of an open-circuit phase fault triggers an immediate transient current spike that briefly reaches 11.5 A before settling at a steady-state value of 10.5 A. To maintain the electromagnetic torque required to track the reference speed with only two remaining operational phases, the PID control system forces the remaining healthy phases to draw a higher magnitude of current.
- Overload Profiling ($t = 3.5$ s): Upon the application of the overload disturbance, the RMS stator current jumps significantly to 12.3 A, surpassing the Rated Current boundary. While the healthy motor response stabilizes just under the rated limit, the cumulative combination

of severe phase imbalance and mechanical overload forces the faulty system into a hazardous overcurrent zone. This sustained overcurrent behavior poses a severe risk of thermal degradation to the stator insulation if left unchecked.

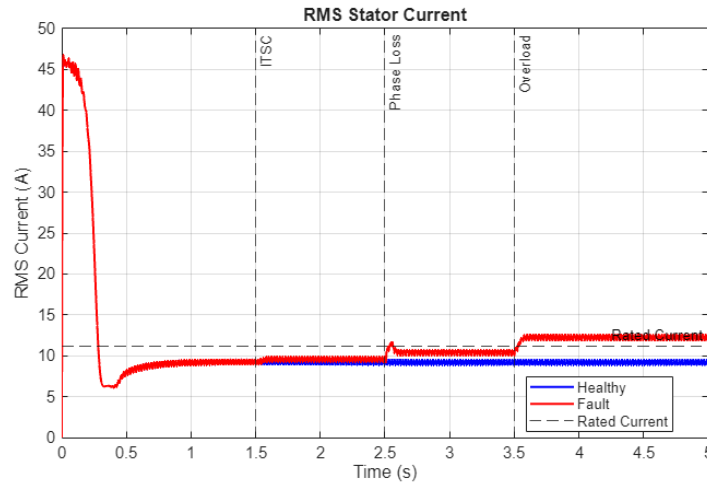


Figure 5: The root-mean-square (RMS) stator current.

The operational degradation profile and the corresponding tracking capability of the proposed prognosis framework are validated through the Predictive Maintenance Health Index trajectory presented in Figure 6. The health index acts as a dynamic indicator, tracking the system's operational integrity against two predefined degradation thresholds: a Warning baseline (1.2) and a Critical baseline (1.5). Under normal operating conditions during the initial transient and startup window ($0 \leq t < 0.5$ s), the index shows a momentary settling curve from an initial value of 2.4 down to a nominal steady-state baseline of approximately 0.95, remaining safely within the healthy zone below both safety thresholds. The sequential injection of anomalies shifts the health index in a distinct, stepped escalation pattern:

- **Inter-Turn Short Circuit (ITSC) Fault ($t = 1.5$ s):** Immediate detection of the winding short circuit causes the health index to jump sharply from 0.95 to 2.9. This sudden transition breaches both the Warning and Critical thresholds simultaneously, highlighting the high severity of internal asymmetrical stator faults.
- **Phase Loss Anomaly ($t = 2.5$ s):** The initiation of the open-circuit phase loss fault drives the degradation indicator even higher, stepping up from 2.9 to 5.75. This secondary surge accurately mirrors the heightened structural stress and heavy torque ripple accumulation observed within the motor drive network.
- **Overload Profiling ($t = 3.5$ s):** Upon applying the mechanical overload, the health index undergoes its final escalation, climbing abruptly to a peak level of 7.85. This severe magnitude marks full-scale operational distress, driven by the cumulative thermal and mechanical strain of operating with severe phase imbalance under overloaded conditions.

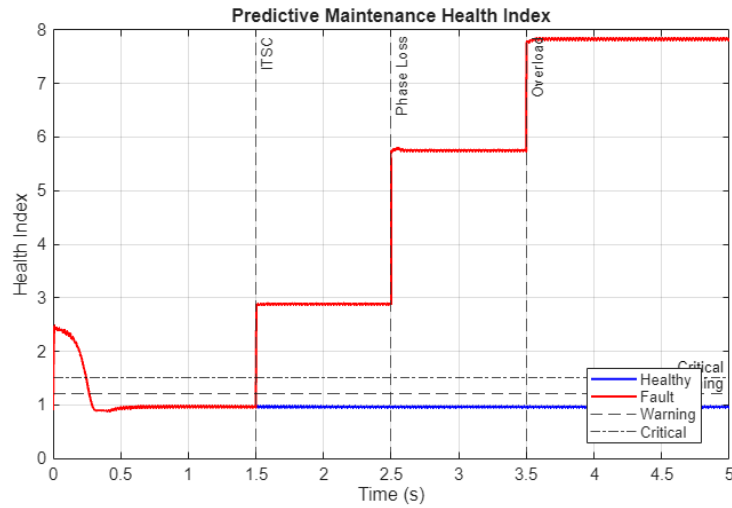


Figure 6: the Predictive Maintenance Health operation.

IV. CONCLUSIONS

This paper successfully developed and validated a multi-signal, model-based fault-prognosis framework for a closed-loop governed three-phase induction motor under the manuscript title: "Fault Analysis and Predictive Maintenance Simulation and Analysis of Induction Motor PID Control Systems." By executing identical parallel simulation paths in MATLAB/Simulink under uniform PID parameters, this study comprehensively exposed the diagnostic vulnerabilities of conventional linear feedback networks when managing multi-domain stator and rotor distress. The principal findings of this research demonstrate that:

- **Controller Masking Effects:** While a classical linear PID loop possesses enough robust error correction to maintain the average target rotor speed (150 rad/s) despite structural failures, it completely masks early fault progression by "shuffling" the tracking deviations back into internal system parameters. This action generates severe, unmitigated high-frequency speed ripples and structural torque pulsations.
- **Cascading Fault Performance:** The injection of an electrical Inter-Turn Short Circuit (ITSC) creates localized asymmetries, broadening torque envelopes without triggering visible speed drops. The open-circuit Phase Loss introduces a sharp transient torque spike up to 23 N·m, forcing the remaining phases to draw an elevated steady-state current of 10.5 A. Ultimately, combined with a mechanical overload, the drive enters a hazardous overcurrent condition of 12.3 A, which crosses the motor's rated current boundary (11 A) and exposes the stator winding to thermal runaway risks.
- **Unified Health Index Effectiveness:** Relying on single-signal diagnostic metrics fails under feedback regulation. However, by establishing a multi-parameter diagnostic vector that fuses speed deviations, torque ripple expansion, RMS current, and THD, the proposed framework can accurately calculate an unmasked Predictive Maintenance Health Index. This health index maps degradation linearly across distinct steps surging distinctly from 0.95 up to 7.85 satisfactorily crossing pre-established Warning and Critical lines.

The clear stepping response of the health index proves that the framework can detect, differentiate, and quantify co-dependent electrical and mechanical anomalies in real time. Future developments will focus on integrating non-linear, fault-tolerant control strategies—such as Adaptive Sliding Mode Control to actively suppress these torque and current pulsations, alongside deploying Fast Fourier Transform (FFT)-based spectrum models to validate these simulated indicators against real-world experimental testbeds.

REFERENCES

1. Al-Barnouti, I. (2001). Human Resource Management: Foundations and Operational Directions (1st ed.). Dar Al-Wael for Publishing.
2. Al-Hiti, K. A. (2005). Human Resource Management: A Strategic Perspective (2nd ed.). Dar Al-Hamed for Publishing and Distribution.
3. Al-Louh, N. (2019). The role of knowledge management in improving the performance of tourism enterprises. *Journal of Economic and Administrative Sciences*, 25(3), 112-135.
4. Al-Sayeh, T. (2016). The role of internal marketing in improving employee performance (Unpublished master's thesis). Faculty of Economic Sciences, University of Algiers.
5. Boukrita, F. (2011). Evaluating organizational performance using balanced scorecard frameworks (Unpublished doctoral dissertation). University of Oran.
6. Derbali, M. (2006). Employee empowerment as a contemporary management paradigm. *Journal of Management and Economics*, 14(1), 1-18.
7. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson Prentice Hall.
8. Idris, W., & Al-Ghalbi, T. (2009). *Strategic Management: Concepts and Applied Case Studies* (1st ed.). Dar Al-Yazouri for Publishing.
9. Kotler, P., & Keller, K. L. (2006). *Marketing Management* (12th ed.). Pearson Prentice Hall.
10. Mansour, A. (2008). *Administrative Communication and its Impact on Service Quality in Service Enterprises* (1st ed.). University Culture House.