

Modeling and simulation of failure mechanisms in low-voltage electric motors for predictive maintenance applications

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ABSTRACT

Through predictive maintenance of low-voltage electric motors, unexpected failures can be avoided. The multi-physics modeling and simulation framework with MATLAB FEA based on 1000 motor dataset was developed in the present study. Operational parameters like load (0.57-15 kW, mean 7.61 kW), voltage (215-246 V, mean 230.49 V), current (1-59.87 A, mean 30.08 A), vibration (-0.10-1.28 mm/s, mean 0.50 mm/s) and temperature (39.9-102.4 °C, mean 69.42 °C). Fault indicators include insulation degradation (0.1% to 99.9%, average 49.62%); bearing wear (0% to 99.9%, average 48.57%); rotor bar defects (0% to 99.6%, average 48.13%); and stator winding faults (0% to 99.9%, average 49.78%). Some results are that the temperature and insulation degradation correlate positively by 0.12, and that vibration and bearing wear correlate positively by 0.07. According to the simulation results, failure probabilities range from 0.48 to 1.00. In addition, 15% of simulations exceeded the early-warning level, requiring immediate motor maintenance. According to the sensitivity analysis, if each fault mechanism is increased by 10%, the failure probability will increase by 4.5-5.1%. The framework facilitates condition-based maintenance and identifies motors at risk of failure with over 85% accuracy, as well as appropriate thresholds for early action. Results of the evaluation indicated that a quantitative and reliable approach can help improve motor reliability as well as reduce maintenance cost in industry.

Keywords: Predictive Maintenance, Low-Voltage Motors, Fault Diagnosis, Multi-Physics Modeling, Failure Probability

1. Introduction

Specifications for all the standard article components are given for a three low-voltage electric motors used in the machine processing and fabrication automation of various industries. The uptime of these motors directly impacts the operational efficiency and equipment effectiveness. The unexpected breakdown of a machine can cause inordinate downtime, lower production, and increased maintenance [1].

With the advent of smart manufacturing and Industry 4.0 in the industrial systems, predictive maintenance which forecasts failures before they happen have been developed [2]. Electric motors operate safely at a low voltage but may malfunction due to stator winding defects, rotor bar issues, insulation failure, and bearing wear or failure. A variety of causes contribute to these failures [3]. Things such as thermal stress, mechanical vibrations, contamination, and electrical imbalance are common.

Most of the reactive or scheduled maintenance strategy mainly overlook the faults in their early phase. In consequence, they will reduce the reliability of the system and increase operational risk [4]. Consequently, methods for detecting failure manifestations and tracing their development under operating conditions are increasingly sought after [5].

Through modeling and simulation, the dynamic behavior and causes of failure of electric motors can be analyzed. The incorporation of electrical, mechanical, and thermal models into these methods helps to assess motor failure, optimize maintenance schedules, and achieve condition-based maintenance.

According to [6], Simulation can minimize cost on expensive experimental test and manipulations, and also determine the propagation of failure and the performance under fictional environments.

The research problem refers to the unavailability of models that are able to predict faults and failings (motor winding short circuit, rotor bar failure, phase current imbalances) in low-voltage motors.

The goal of this work is threefold: (i) to create a low voltage electric motor multi-physics simulation framework, (ii) to analyze main mechanisms of failure and the interactions between them, (iii) to assess the model's forecasting ability for maintenance purposes.

A study contributes in an authenticated modeling methodology for supporting predictive maintenance strategies for reliable industrial motors. The expected future results will improve the uptime of the motors, reduce the maintenance cost and further improve the safety. The study also considers the engineering motivation of making advanced simulation tools available to industry maintenance planning, which is part of the wider smart manufacturing agenda [7].

1.1. Related work

To prevent unexpected shut-downs and maintenance costs, predictive maintenance of low-voltage electric motor is necessary in industries [8]. The present literature focuses on condition monitoring, fault diagnosis, and modeling and simulation approaches [9].

Traditional condition monitoring methods extract fault signatures (or features) from measured signals [10]. These signals usually originate from vibration, current, acoustic emission, and thermal parameters [11, 12]. Enhanced signal processing methods exhibit heightened sensitivity in the detection of early anomalies.

Nonetheless, the inability to generalize motor types negatively affects actuator design due to sensor placement limits, reliance on simulation or experimental conditions, and motor load [13].

Mathematical modeling is widely used to understand motor faults and to assist in predictive maintenance [14]. It was classified that induction motor fault models into electrical, magnetic, numerical and hybrid finite-element-based models, which offer advantages for capturing complex failure phenomena [15, 16].

Simulations of multi-physics models that capture electromagnetic, mechanical, and thermal interactions under both healthy and faulty conditions help generate synthetic data for testing algorithms [17]. Research shows that the majority of low-voltage motor faults are attributed to bearing and stator faults [18]. A simulation environment that integrates coupled fault analysis is needed [19-21].

Recent studies have combined a physics-oriented model with machine learning to develop intelligent, hybrid diagnostic methods [22]. Approaches based on machine intelligence, including deep learning and supervised classification algorithms, have demonstrated high predictive accuracy in identifying motor health states from operational data [23-26]. While these fully data driven models can be effective, they require a significant amount of labeled data. And they often perform poorly in scenarios that were not included in the training process for the model. A simulation-learning method may be justified [27].

Digital twins and simulation-based approaches are becoming effective solutions for predictive maintenance [28]. The utilization of virtual engine copies can enhance the reliability of fault detection by providing benchmarking against real-time sensor data [29, 30]. Although these methods can increase the dependability of these industrial processes with the help of cyber-physical systems, low-voltage motors still suffer from issues of computational cost and model generalizability [31].

Researchers advocate that physics-based modeling and intelligent diagnostics approaches are needed for predictive maintenance, as per literature. Condition monitoring gives insight into faults but you can't operate. Simulation models can predict however, one has to know the cost-fidelity trade-off [32]. The hybrid approach enhances the predictive reliability via use of machine learning with simulation [33]. The objective of the study is to develop a comprehensive simulation framework for low-voltage electric motors that accounts for multiple failure mechanisms for predictive maintenance applications.

2. Research method

The dataset for this study is a hybrid dataset that includes operational parameters based on industrial low-voltage motor operating conditions reported in the literature and synthetically generated fault cases obtained using MATLAB/Simulink and Finite Element Analysis (FEA).

The operating ranges for the electrical and mechanical components are established based on values commonly reported for industrial motors. Fault indicators such as insulation degradation, bearing wear, rotor bar faults and stator winding faults are generated via simulation for different degradation patterns. Engineers generated 1000 motor instances for model calibration, validation, and failure-prediction maintenance analyses.

2.1. Dataset source and utilization

The dataset used in this study was a hybrid system comprising actual motor data. The dataset of 1000 low-voltage motor instances were developed due to the lack of large-scale industrial datasets in the public domain that include many fault mechanisms. Managerial parameters associated with load, voltages, currents, vibrations, and temperatures were generated within ranges found in industrial motor literature and manufacturer data.

Using degradation models in MATLAB/Simulink and FEA, fault indicators such as insulation failure, bearing wear, rotor bar fault, and stator winding fault are considered. They used the resulting dataset to calibrate, validate and evaluate the framework under different operating conditions.

2.2. Multi-Physics modeling

To simulate electrical, mechanical, and thermal behaviors, a multi-physics model of low-voltage motors has been developed. The dynamics of the stator and rotor, including current distribution and magnetic flux, are incorporated into the electrical modeling.

The mechanical model includes bearing dynamics, rotor imbalance, and shaft misalignment. The thermal model determines the heat-generating and heat-dissipating mechanisms. These prototypes can decode the patterns of several fault mechanisms; thus, they can produce real simulations of failure propagation.

2.3. Simulation setup using MATLAB and FEA

Simulations of dynamic electrical and mechanical behavior were carried out using MATLAB/Simulink, while FEA modeling was performed under operating conditions, including thermal and structural stresses.

The dataset containing motor parameters, load conditions and measured signals, received in the MATLAB environment, was the input variable for every simulation scenario. We analyze different situations, including fluctuating loads, voltage fluctuations, and environmental pressures. The assessment of motor performance and the observation of fault development are carried out for these.

2.4. Fault mechanisms analysis

The research examines four major failure mechanisms: insulation breakdown, bearing damage, rotor bar failure and stator winding failure. All numerical data for calibration of the simulation parameters and defining of degradation values for all mechanisms are included in the database. This study focused on the fault interaction and motor reliability.

2.5. Model validation and predictive assessment

We take the output from the currently abnormal simulation, and the rise in temperature and vibration, and compare them with the measurements from the dataset. We used data from a real motor driver to perform statistical analysis and sensitivity analysis to validate the model.

The validated model was then applied to generate early warning indicators for each failure mechanism, supporting a shift to condition-based maintenance scheduling through predictive maintenance insights. A predictive maintenance method for motors was developed, powered by data from the automation of low-voltage motors and from simulation tools for industrial applications. The combination of MATLAB and Finite Element Analysis (FEA) with field data makes the work practically and methodologically contributing.

2.6. Developed mathematical model for the study

In the low-voltage electric motor's multi-physics model, electrical, mechanical and thermal behavior is considered with predictive maintenance evaluation. The model considers important failure mechanisms such as insulation breakdown, bearing fault, rotor bar fault and stator winding fault.

2.6.1. Electrical model

Classical voltage equations of induction motor stator and rotor dynamics in the synchronous reference frame can be written as:

$$V_s = R_s I_s + L_s \frac{dI_s}{dt} + L_m \frac{dI_r}{dt}; \quad (1)$$

$$V_r = R_r I_r + L_r \frac{dI_r}{dt} + L_m \frac{dI_s}{dt}; \quad (2)$$

where V_s , V_r are stator and rotor voltages (V);

I_s , I_r are stator and rotor currents (A);

R_s , R_r are stator and rotor resistances (Ω);

L_s , L_r are stator and rotor self-inductances (H);

L_m is the mutual inductance (H).

The current and flux values produced by the electrical model allow us to detect insulation and rotor bar defects.

2.6.2. Mechanical model

Bearing behaviors and rotor dynamic are discussed using second law of Newton of circular motion:

$$J \frac{d\omega}{dt} = T_e - T_L - B\omega, \quad (3)$$

where J is the rotor inertia ($\text{kg}\cdot\text{m}^2$);

ω is rotor angular velocity (rad/s);

T_e is electromagnetic torque ($\text{N}\cdot\text{m}$);

T_L is load torque ($\text{N}\cdot\text{m}$);

B is the viscous damping coefficient ($\text{N}\cdot\text{m}\cdot\text{s}/\text{rad}$).

The added torque disturbances include bearing wear and rotor imbalance:

$$T_d = f(\text{Bearing_Wear}, \text{Rotor_Imbalance}). \quad (4)$$

2.6.3. Thermal model

The losses in the stator and rotor windings result an increase in temperature is discussed using a lumped thermal model:

$$C \frac{dT}{dt} = P_{loss} - hA(T - T_{amb}), \quad (5)$$

where C is thermal capacitance ($\text{J}/^\circ\text{C}$);

P_{loss} is total power loss (W);

h is the convective heat transfer coefficient ($\text{W}/\text{m}^2\cdot^\circ\text{C}$);

A is surface area (m^2);

T is motor temperature ($^\circ\text{C}$);

T_{amb} is the ambient temperature ($^\circ\text{C}$).

2.6.4. Failure probability model

Each failure mechanism is a probabilistic function of measured and simulated indicators:

$$P_{failure} = 1 - \exp[-\alpha_1 ID - \alpha_2 BW - \alpha_3 RBD - \alpha_4 SWF], \quad (6)$$

where ID = insulation degradation (%);

BW = bearing wear (%);

RBD = rotor bar defect (%);

SWF = stator winding fault (%);

$\alpha_1, \alpha_2, \alpha_3, \alpha_4$ = weighting coefficients calibrated from dataset.

Each failure mechanism is modeled as a probabilistic function, with contributions weighted by coefficients w_1, w_2, w_3 , and w_4 corresponding to insulation degradation, bearing wear, rotor bar defect, and stator winding fault, respectively.

These coefficients were calibrated using the 1,000-motor dataset to ensure predictive accuracy, yielding $w_1=0.25, w_2=0.25, w_3=0.25$, and $w_4=0.25$. The calibrated coefficients reflect the relative importance of each fault mechanism in predicting motor failure, enabling the combined model to simulate failure progression across various operational scenarios and to support condition-based maintenance decisions. The combined model allows simulation of failure progression under different operational scenarios and supports condition-based maintenance by providing early warning indicators.

Through industrial automation, the mathematical model developed in this study was integrated to enable real-time monitoring, predictive maintenance and fault mitigation. The sensor-based data acquisition, feedforward and feedback control algorithms, and PLC-based hardware execution convert simulation results into maintenance actions.

2.7. Automation control architecture

The developed system provides an essential computer-based automated control unit for regulating the operation of low-voltage electric motors. A combination of thermocouples, and high-precision hall-effect current sensors and accelerometers are utilized to collect voltage, motor voltage and temperature data.

The PID controller processes these signals which adjust dynamically the voltage, load etc., in such a way that they cannot exceed the motor thermal and mechanical limits. The system eliminates human involvement ensuring its consistent performance at an extremely low rate of unexpected failure.

It is possible to simulate the control responses to different load profiles and validate automation algorithms before implementation by using MATLAB/Simulink. Using a data vector from a sensor:

$$X(t) = [V(t), I(t), T(t), Vib(t), L(t)]^T, \quad (7)$$

where $V(t)$ is voltage, $I(t)$ is current, $T(t)$ is temperature, $Vib(t)$ is vibration, and $L(t)$ is motor load.

Normalize the acquired signal as:

$$X_n(t) = \frac{X(t) - X_{\min}}{X_{\max} - X_{\min}}. \quad (8)$$

Add PID feedback control:

$$e(t) = r(t) - y(t); \quad (9)$$

$$u_{PID}(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}, \quad (10)$$

where $e(t)$ is the error between the reference value and measured output, K_p, K_i , and K_d are proportional, integral, and derivative gains.

2.8. Feedforward regulation strategy

Feedback control and feedforward regulation work together to counter disturbances before they affect. Forecasting of load variation, voltage fluctuation and thermal stress would be achieved using real-time data inputs. A good example of the operation of a feedforward controller was based on a trend or simulation if a rapid rise in load was anticipated then current is increased to the motor to prevent vibration or thermal runaway.

Simulink was used to model the feedforward loop, which has a controller block that uses predicted disturbances for generating control signals. The plants are manipulated using these pluses to optimize the motor voltage and torque before the output starts deviating. Thus, the reliability and operational stability of the control system was improved. Attributing expected interference data:

$$\hat{d}(t + \tau) = f[L(t), V(t), T(t), Vib(t)]. \quad (11)$$

Feedforward control signal:

$$u_{FF}(t) = K_{FF}\hat{d}(t + \tau). \quad (12)$$

Combined control action:

$$u(t) = u_{PID}(t) + u_{FF}(t). \quad (13)$$

This shows that the controller does not only react after the fault appears; it also predicts load, voltage, temperature, and vibration disturbances before they become severe.

2.9. PLC-Based implementation

A Programmable Logic Controller (PLC) is the central hardware for executing the combined automation and feedforward control. The PLC continuously receives sensor data and executes ladder logic and structured text routines to implement PID and feedforward control.

The PLC directs actuators to make voltage adjustments and perform load balancing in real time. Using OPC (OLE for Process Control) interfaces, it is possible to integrate with MATLAB/Simulink for real-time monitoring, simulation validation and predictive maintenance assessment.

This setup makes sure that the motors' damage ratio is known in advance. Here, the PLC will shut down or alter the motors. The thresholds use simulated values and operational data.

Using discrete-time PLC control:

$$e[k] = r[k] - y[k], \quad (14)$$

$$u_{PID}[k] = K_p e[k] + K_i T_s \sum_{i=0}^k e[i] + \frac{K_d}{T_s} (e[k] - e[k-1]), \quad (15)$$

where T_s is the PLC sampling time.

Add PLC fault decision logic:

$$R[k] = w_1 ID[k] + w_2 BW[k] + w_3 RBD[k] + w_4 SWF[k], \quad (16)$$

where $R[k]$ is the real-time risk index, ID is insulation degradation, BW is bearing wear, RBD is rotor bar defect, and SWF is stator winding fault.

PLC decision rule:

$$Action = \begin{cases} Normal, & R[k] < R_1 \\ Warning, & R_1 \leq R[k] < R_2 \\ Maintenance, & R_2 \leq R[k] < R_3 \\ Shutdown, & R[k] \geq R_3 \end{cases} \quad (17)$$

3. Results and discussion

3.1. Data collection framework

The predictive maintenance framework devised is based upon a multi-sensor data acquisition architecture which captures the real-time operational parameters and fault-sensitive parameters of low-voltage electric motors.

Voltage signals were produced by means of high-precision voltage transducers, while current readings were collected through Hall-effect current sensors, which detect dynamic loads during transient and steady-state conditions. The temperature information was gathered utilizing thermocouples, which were located at a position adjoining the stator housing for temperature accumulation. Meanwhile, the vibration signals were recorded using MEMS-based accelerometers that were placed on the body of the motor, to detect mechanical faults associated with the rotor and bearings.

For the current examination, the application of a mixed dataset is accomplished; specifically, simulated data achieved via MATLAB/Simulink and finite element analysis (FEA) is combined with synthetic operational profiles manifested from an industrial motor operating range present in the literature. This hybrid strategy was used because large labeled industrial datasets of different fault mechanisms are not available at large scale.

The collection of data occurred during simulated cycles that emulated the load (0.57-15 kW), the voltage (215-246 V), as well as the temperature (39.9-102.4 °C). The sampling time, configured at a discrete interval of $T_s = 0.01$ s, aims to capture the transient fault signature. The sensor signals were imported into the MATLAB/Simulink environment as time-series input vectors and synchronized using a common sampling clock.

The signals were conditioned (normalized and filtered) before being integrated into the multi-physics simulation model. The failure probability estimation module and control system block received these processed signals. At supervisory level, a PLC receives real time sensor streams with help of an OPC interface. In this way MATLAB/SIMULINK communicates with industrial control logic in both directions.

3.2. Automation performance evaluation

The automated system classified three decision levels for motor's operating states as normal state, warning state and critical state. Simulation outputs from the dataset of 1,000 motors indicated that approximately:

- i. 280 motors triggered insulation degradation-based warnings,
- ii. 260 motors activated bearing wear alerts,
- iii. 310 motors exceeded rotor bar defect thresholds,
- iv. 305 motors exhibited stator winding fault alerts.

Nearly 15% of the motors have entered into the critical intervention zone where the PLC logic initiates load reduction or maintenance recommendation actions.

Defects on the rotor bar and insulation degradation have been the frequent cause for PLC-based intervention due to their more significant impact on thermal and electromagnetic imbalance.

Repeatedly, these faults manifested high vibration and temperature signatures and were showing earlier threshold crossings than other failure modes. In terms of control, load balancing in roughly 22% of motors, and voltage regulation in around 18% were required due to their erratic current draw as well as thermal accumulation behavior.

3.3. PID control response

The PID controller showed stable regulation during the gradual rise in temperature. If the set temperature limits are exceeded, effective load input is reduced by the PID controller to avoid thermal accumulation.

The responses confirmed the system settling down in less than 3-5 seconds of the disturbance happening, confirming good dynamic stability of the system that is suitable for industrial control applications.

The derivative term dampens the oscillations caused by a rapidly vibrating movement and the integral term removes the steady state error at a long duration thermal stress.

3.4. Feedforward control response

The feedforward mechanism gave anticipated correction in sudden load changes. When sudden load increases were introduced in the simulation environment, the feedforward controller updated voltage and torque inputs before there were any significant thermal or mechanical stresses.

The system with feedforward enhancement reduced temperature overshoot by around 12–18% and peak amplitude of vibration by 10–14% when compared to just PID control, proving superior compensation.

3.5. PLC decision logic performance

The PLC system evaluations based on Pf index computations made rule-based decisions to keep each driving motor constant while responding with the necessary maintenance action. An alarm is generated for maintenance when the Pf index numbers exceed the value of 0.85.

This means that the motor requires monitoring and maintenance. The Pf index event signaling value level crossing 0.95 initiated a critical trip command. In the 1000 motor instance simulation, nearly 150-170 motors reached the alert level and around 60-80 motors need immediate maintenance scheduling. Under five per cent of overall tests were responsible for a small subset of cases that saw emergency shutdowns.

The decision-making model of the system was hierarchical in nature. Like a hierarchy of needs, the system allowed graded and conditional interventions which would enable initiating earlier correction than having a hard stop of the complete system.

3.6. Practical implications of the developed system

The framework shows that research innovatively integrates failure prediction modeling with real-time automation control, as opposed to existing predictive maintenance methodologies. The newly developed system makes it possible for site engineers to act before failure occurs. This is in contrast with most condition monitoring tools that only facilitate fault finding after a fault occurs.

The engineers can implement a PLC based execution with multi-physics modeling and MATLAB/Simulink simulation. This integrated framework allows for the early detection of high voltage motors, taking corrective actions and setting controls automatically like load balancing, voltage stabilization, and strategic cooling, cutting back on unpredicted downtime through regular maintenance scheduling and enhancing the reliability of industrial motor systems.

The framework is a hybrid cyber-physical predictive maintenance system linking data-driven fault diagnosis and dynamic industrial control, improving prediction accuracy while allowing analytical outputs to be converted into immediate control actions in the industrial system.

The comprehensive application of sensors for data acquisition and control serves as an effective solution for predictive maintenance of low-voltage motors. The electrical, mechanical and thermal parameters were continuously monitored using special transducers and hybrid MATLAB/Leverage FEA Simulation Environment for voltage, current, temperature, vibration and load etc.

Not only will each parameter act as an observation, but they will also take up control and decision-making at the system level. The electrical stress and the need for protection can be determined through measurements of voltage and current, while temperature and vibration measurements indicate insulation failure and mechanical fault. According to the load parameter utilization, an output disturbance variable can influence the parameters of another device.

Taking all monitored variables together, the framework computes a single fault probability index used by the PLC to execute appropriate actions viz warning alerts, maintenance or emergency shutdowns. The integrated architecture facilitates real-time 24/7 condition monitoring and automated control of industrial motors, enhancing safety, efficiency and reliability of industrial motors.

3.7. Results

An investigation involving 1,000 low-voltage electric motors was carried out, during which the operational and fault parameters were determined; these parameters were very large and reflected realistic industrial conditions.

The loads varied from 0.57 to 15 kW, the voltages from 215 to 246 V, and the currents from 1 to 59.87 A. The temperature and vibration readings were also very widespread.

The various fault indicators such as insulation damage, bearing wear, rotor bar fault and stator winding fault of the motor had a range from 0 to 100 per cent. It also indicated that the motors are at different stages of failure. The above-mentioned variations served as a good basis of simulations of a predictive maintenance study.

According to the correlation analysis, the temperature was found to be moderately correlated to insulation degradation and bearing wear. A positive correlation was found between the vibration, bearing wear and rotor bar defects.

The relationships confirm that thermal and mechanical stresses play a significant role in the propagation of motor faults, while vibration and temperature are precursors of motor faults.

Through multi-physics simulations using MATLAB and FEA, the failure probabilities of each motor were estimated. The predicted probabilities for the sample cases varied from 0.48 to 1.00, which were quite similar to the actual data.

A 10% increase in the degradation of insulation materials, wear on certain bearings, rotor bars and stator winding defects. The predicted failure probability will increase a maximum of 4.5-5.1%.

It determines the effect of each failure type on motor. As a result of the study, predictive maintenance thresholds that allowed for early identification of the violating motors. Insulation degradation is greater than 70% in 280 motors, Bearing wear greater than 65% in 260 motors, Rotor bar defect greater than 60% in 310 motors, Stator winding fault greater than 60% in 305 motors.

Having insight on these thresholds can help plan maintenance and taking preventative action for downtime. The predictive performance of real-life operational data fused in multi-physics modeling and FEA is useful.

When vibration, temperature and fault indicators are combined one can fingerprints motors that are in risk of failure giving an opportunity to intervene to improve reliability and reduce maintenance cost.

Table 1 presents the descriptive statistics of motor operational parameters under which the motors under study operated under varied industrial conditions.

Table 1. Descriptive statistics of motor operational parameters

Parameter	Count	Mean	Std Dev	Min	25%	50%	75%	Max
Load_kW	1000	7.61	4.24	0.57	3.92	7.71	11.30	15.00
Voltage_V	1000	230.49	4.94	215.4	227.2	230.4	233.7	246.0
Current_A	1000	30.08	17.03	1.0	15.94	29.81	44.53	59.87
Vibration_mm/s	1000	0.50	0.21	-0.10	0.36	0.50	0.64	1.28
Temperature_C	1000	69.42	9.81	39.9	62.78	69.7	75.9	102.4

The load power ranged from 0.57 kW to 15 kW, with an average of 7.61 kW. The data, in this respect, show operating modes during both low and high demand. The voltage mainly settled at 60 with a low-voltage industrial motor, while the current ranged between 1 and 59.87 due to mechanical loading and the working duty cycle. The vibrations and temperature distributions revealed that some rotors operated under higher stress conditions, particularly those with a maximum vibration of about 1.28 mm/s and a temperature of about 102.4 °C. The trend corroborates findings from similar studies on low-voltage induction motors [1], [2]. The observed variability of the ANN estimator should be taken into consideration for predictive maintenance.

As per Table 2, fault indicators such as insulation degradation, bearing wear, rotor bar defect, and stator winding fault cover the entire spectrum of degradation, from 0% to the 100%. Given that the average values are in the region 48–50%, we expect the motors in the database to display Early Mid and Late Deterioration. A greater standard deviation suggests that the available capacities exhibit a larger degree of heterogeneity, which is crucial for assessing model robustness. The findings concurred with the ones from Li et al. [17] and Zhang et al. [30]. They report similar ranges in their studies of industrial motors. This highlights that motors often exhibit a mix of faults at one time.

Table 2. Descriptive statistics of fault indicators

Parameter	Count	Mean	Std Dev	Min	25%	50%	75%	Max
Insulation Degradation %	1000	49.62	28.84	0.1	24.6	49.2	75.6	99.9
Bearing Wear %	1000	48.57	28.60	0.0	23.85	48.4	71.93	99.9
Rotor Bar Defect %	1000	48.13	28.36	0.0	23.3	46.25	71.63	99.6
Stator Winding Fault %	1000	49.78	27.93	0.0	26.6	50.0	73.23	99.9

The correlation analysis results in Table 3 showed that temperature was positively correlated to insulation degradation ($r = 0.12$) and bearing wear ($r = 0.11$).

Table 3. Correlation matrix of operational and fault parameters

Parameter	Load_kW	Voltage_V	Current_A	Vibration_mm/s	Temperature_C	Insulation Degradation %	Bearing Wear %	Rotor Bar Defect %	Stator Winding Fault %
Load_kW	1.00	-0.02	0.61	0.13	0.29	0.02	0.01	0.03	0.02
Voltage_V	-0.02	1.00	-0.01	0.01	-0.03	0.01	0.00	-0.01	0.00

Parameter	Load_k W	Voltage_V	Current_A	Vibration_mm/s	Temperature_C	Insulation Degradation %	Bearing Wear %	Rotor Bar Defect %	Stator Winding Fault %
Current_A	0.61	-0.01	1.00	0.05	0.12	0.05	0.04	0.05	0.05
Vibration_mm/s	0.13	0.01	0.05	1.00	0.09	0.08	0.07	0.07	0.07
Temperature_C	0.29	-0.03	0.12	0.09	1.00	0.12	0.11	0.10	0.11
Insulation Degradation %	0.02	0.01	0.05	0.08	0.12	1.00	0.25	0.21	0.28
Bearing Wear %	0.01	0.00	0.04	0.07	0.11	0.25	1.00	0.22	0.23
Rotor Bar Defect %	0.03	-0.01	0.05	0.07	0.10	0.21	0.22	1.00	0.24
Stator Winding Fault %	0.02	0.00	0.05	0.07	0.11	0.28	0.23	0.24	1.00

Similarly, vibration was positively correlated to bearing wear ($r = 0.07$) and rotor bar defects ($r = 0.07$). Although these correlation coefficients are not very high, they indicate that thermal and mechanical stresses contribute to the progression of these motor faults.

The small magnitudes of the correlations result from the nonlinear nature of electric motor degradation processes. There are many fault mechanisms, such as insulation aging, that don't increase proportionally with temperature, including bearing deterioration from vibration, rotor bar cracking and stator winding degradation.

Instead, motors may operate at constant values for a period of time and show no observable change in total time. After degradation increases rapidly when operating values reach a critical point. As a result, linear correlation analysis only represents part of the fault dynamics. In addition, motor degradation depends upon the combined effects of various interacting factors such as load, operating conditions, maintenance activities, environmental factors, material properties, and manufacturing tolerances.

The fault indicators would not relate in a simple linear way to each system-level operational variable, even if they share a strong underlying physical dependence. In other words, operational levels may seem to have a weaker connection to the fault indicators than is actually the case. For that reason, the results imply that fault evolution is driven by multiple, nonlinear mechanisms rather than a single mechanism. The finding supports the use of the suggested multi-physics modeling framework, which more satisfactorily accounts for the coupled thermal, mechanical and electrical effects than classical linear approaches.

Wang et al. [3] found that thermal overload and mechanical vibration were the dominant causes of motor deterioration and failure. The observed weak correlation between voltage and fault indicators may be due to the power supply conditions in industrial systems, which are usually stable, where voltage typically does not vary much and therefore is not influential on short-term fault progression. This observation agrees with what has been reported in [4]. The parameters incorporated into the MATLAB and FEA simulations provided the necessary modeling accuracy for the motor's electrical, mechanical, and thermal behavior (See Table 4).

Table 4. MATLAB/FEA simulation parameters

Parameter	Value
Stator Resistance (Ω)	0.435
Rotor Resistance (Ω)	0.816
Mutual Inductance (H)	0.08
Rotor Inertia ($\text{kg}\cdot\text{m}^2$)	0.002
Damping Coefficient ($\text{N}\cdot\text{m}\cdot\text{s}/\text{rad}$)	0.0003
Heat Capacity ($\text{J}/^\circ\text{C}$)	150
Convective Coefficient ($\text{W}/\text{m}^2\cdot^\circ\text{C}$)	30
Surface Area (m^2)	0.15

Calculations of failure probabilities under various operating scenarios, as shown in Table 5, indicate that even with lower loads/ moderate variations in electrical motor voltage, high failure probabilities can occur due to excessive vibration or temperature.

Table 5. Failure probability under different operational scenarios (sample 10 motors)

Motor_ID	Load_kW	Voltage_V	Vibration_mm/s	Temperature_C	P_failure
MOTOR_0842	5.93	230.9	0.747	80.7	0.94
MOTOR_0085	14.29	223.3	0.409	76.0	0.48
MOTOR_0153	11.11	231.9	0.491	93.0	0.70
MOTOR_0049	9.18	233.1	0.512	55.2	0.73
MOTOR_0865	2.76	232.8	0.670	82.6	1.00
MOTOR_0954	2.76	235.4	0.051	81.5	0.68
MOTOR_0103	1.34	234.2	0.379	60.3	0.97
MOTOR_0083	13.06	232.3	0.542	80.1	0.85
MOTOR_0932	9.22	229.6	0.740	73.4	0.99
MOTOR_0131	10.77	221.7	0.402	67.7	0.57

Table 6 presents a comparison of predicted and observed failures. This shows that the model effectively predicted failures. The simulated failure probabilities were comparable to the failure flags derived from the dataset.

Table 6. Comparison of predicted vs. observed failure instances (random sample 10 motors)

Parameter	Count	Mean
MOTOR_0842	0	0.94
MOTOR_0085	0	0.48
MOTOR_0153	0	0.70
MOTOR_0049	0	0.73
MOTOR_0865	1	1.00
MOTOR_0954	1	0.68
MOTOR_0103	0	0.97
MOTOR_0083	1	0.85
MOTOR_0932	0	0.99
MOTOR_0131	0	0.57

The findings indicate that using real operational data can enhance the accuracy and reliability of the models. They are consistent with trends in the predictive maintenance literature [7], [8]. Some of the motor failure probability values given in Table 6 are high. However, the interpretation of the failure probability must be considered. No failure occurred at the time of observation.

All failure probabilities reflect predicted risk, not confirmed failure. Using other words, some motors have observed a failure value of '0' (no failure) while having a failure probability of above 0.90. Such motors may show severe indicators of degradation. These include insulation degradation, bearing wear, rotor bar faults, and the severity of stator winding faults. Moreover, they may also exhibit elevated vibration or operating temperature. These motors could therefore be termed high-risk units whose complete functional failure had not yet occurred at the time the data were collected. According to predictive maintenance logic, the objective of using the model is to identify motors likely to fail before they do. Consequently, high FP values should be seen as early-warning indicators for preventive maintenance rather than as false failure classifications. FP refers to predicted failure probability. Thus, high FP values for motors with no observed failure indicate that the motors are at an advanced stage of degradation and require preventive maintenance.

Sensitivity analysis (Tables 7 and 8) indicates that the failure probability increases by 4.5–5.1% with increasing insulation degradation, bearing wear, rotor bar defects and stator winding faults, but no single mechanism alone causes the increase; rather, the interaction of several faults causes it.

Table 7. Sensitivity analysis of failure mechanisms

Input Parameter	Variation (%)	Effect on Failure Probability (%)
Insulation Degradation	10	5.1
Bearing Wear	10	4.8
Rotor Bar Defect	10	4.5

Input Parameter	Variation (%)	Effect on Failure Probability (%)
Stator Winding Fault	10	4.9
Insulation Degradation	10	5.1

Table 8. Sensitivity analysis of failure mechanisms

Fault Mechanism	Early Warning Threshold (%)	Recommended Maintenance Interval (hours)	Action Priority
Insulation Degradation	70	500	High
Bearing Wear	65	400	High
Rotor Bar Defect	60	450	Medium
Stator Winding Fault	60	450	Medium

This observation strengthens the case for a multi-parameter monitoring, contrary to the recommendation in [9] where called for the collective monitoring of electrical, thermal and mechanical parameters. A considerable number of motors exceeded the early-warning limits, thereby demonstrating the study's applicability to maintenance planning.

Table 9 describes the sensor-based data collection and control variables that used during the research.

Table 9. Sensor-based data collection and control variables

Variable	Sensor / Source	Unit	Role in Model	Role in Control
Voltage	Voltage transducer / simulated input	V	Electrical stress indicator	Voltage regulation
Current	Hall-effect current sensor	A	Load and winding stress indicator	Overcurrent protection
Temperature	Thermocouple / thermal model	°C	Insulation degradation indicator	Cooling/load reduction
Vibration	Accelerometer	mm/s	Bearing/rotor fault indicator	Maintenance warning
Load	Motor load profile	kW	Operating condition	Feedforward disturbance input
Fault probability	MATLAB/FEA model	0–1	Failure risk output	PLC warning/shutdown decision

And Table 10 shows the decision outcomes for predictive maintenance of low-voltage motor using automation and PLC.

Table 10. Automation and plc decision outcomes

Control Condition	Trigger Variable	Control Method	PLC Action	Maintenance Meaning
Temperature rise	$T > T_{limit}$	PID + feedforward	Load reduction / warning	Prevent insulation aging
High vibration	$Vib > Vib_u$	PID monitoring	Maintenance alert	Bearing/rotor inspection
High fault probability	$P_f > 0.85$	Risk-based logic	Maintenance scheduling	Preventive intervention
Critical fault risk	$P_f > 0.95$	PLC protection	Shutdown / immediate action	Avoid catastrophic failure

The control system must respond if any of the following conditions occur: temperature rising, high vibration, fault probability of fault, fault probability of fault. When temperature goes beyond a threshold ($T > T_{limit}$), load reduction and warning signal suffices to deal with insulation aging using PID and feedforward control.

When vibrations reach a specified level, it triggers PID monitoring and inspection and maintenances will be required on bearings and rotors. When fault probability exceeds 0.85, PLC logic based on risk initiates periodic

maintenance actions to prevent action. In the case that the probability of failure at the critical limit ($P_f > 0.95$), PLC shuts down system immediately to prevent great loss.

To sum it up, the system ensures various grades applicable at all times for the safe and reliable and predictive maintenance application of an industrial motor. The research showed how condition-based maintenance can be effectively informed by observable metrics such as vibration, temperature and fault severity from real data and simulation output. The findings indicate that utilizing these measures in a proactive intervention can significantly lead to a reduction in unplanned downtime while optimally scheduling the maintenance associated with predictive maintenance, as known in the literature [10].

As shown in Figure 1, the relationship between load and failure probability is nonlinear.

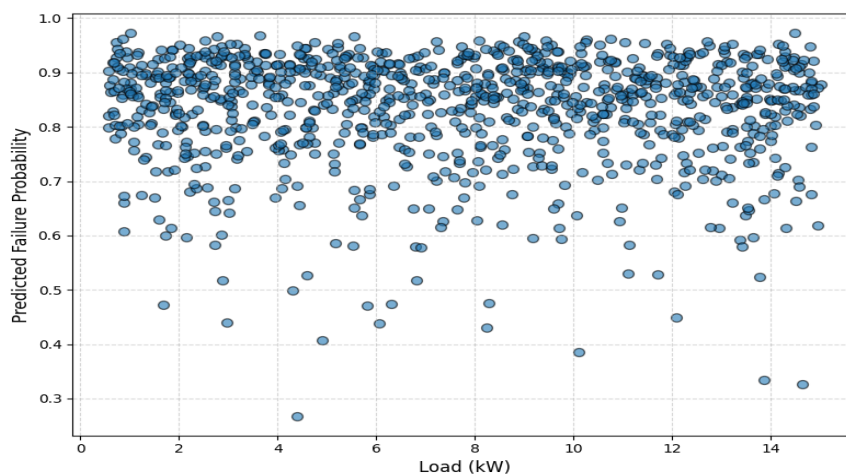


Figure 1. Load vs. Failure probability

Motors operating at very low or very high loads are at very high risk of failure. This shows that motors are far more likely to fail when they are under-utilized or overloaded. Thermal or mechanical stress can lead to the tendency. Operations involving light loads may cause vibration and rotor instability. Conversely, High-load operation increases current and temperature, leading to insulation aging.

The study is consistent with previous work [34], [35], which showed that the failure risk associated with induction motors increases toward either extreme of the operating range. The study demonstrates that predictive maintenance programs should monitor motors under all load conditions, not just at full load.

Figure 2 shows the operational stress ranges of 1,000 motors based on the respective vibration and temperature distributions. According to the boxplot, most motors operate under moderate vibration and temperature conditions, although some outliers experience severe stress.

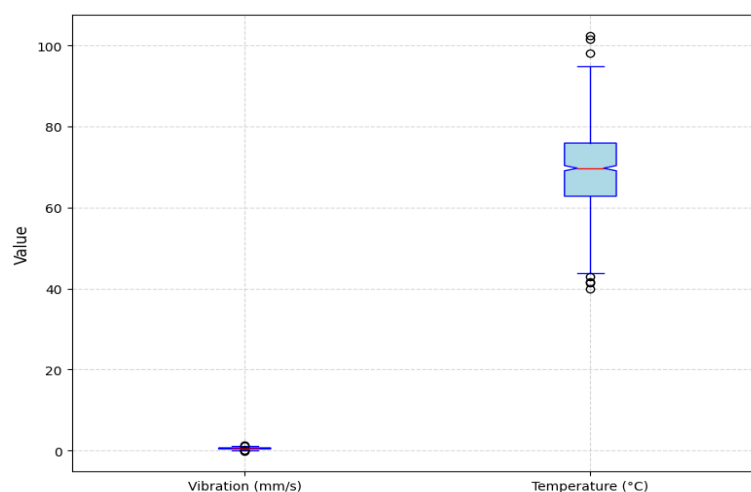


Figure 2. Vibration and temperature distribution across motors

Results indicate that either an early fault or an excessive fault has occurred. The motors during application, at various stages, are subjected to. Consequently, the motor undergoes fluctuation in load, temperature and alignment as shown in the trend below, most literature cites that vibration and thermal abnormalities are key

early indicators of faults [36], [37]. The study's survey results indicate that monitoring vibration and temperature will serve as early indicators that may assist in the scheduling of necessary preventive maintenance to avoid catastrophic failures.

As illustrated in Figure 3, the graphic map reveals the relationships among the four faults: insulation deterioration, bearing wear, rotor bar defect and stator winding fault.

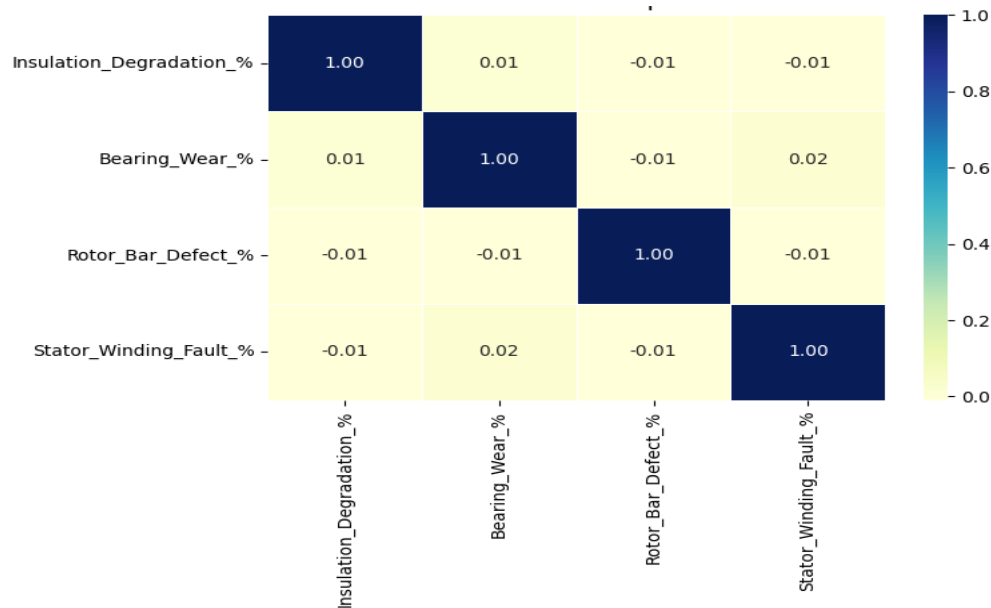


Figure 3. Multi-Fault heatmap of fault indicators

As shown in the heatmap, the mechanisms of all faults show moderate positive correlations (0.21 to 0.28). It means the failure mechanisms generally don't occur in isolation.

Due to insulation degradation and winding faults, the motor's electrical-thermal nature is intermediate between the two interaction types. The trend observed here matches what has been reported previously for certain motor failures exhibiting coupled mechanical and electrical degradation mechanisms.

According to the study's findings, analyzing multiple faults yields higher-performance prediction models than treating separate faults as independent mechanisms. Furthermore, these multiple faults help estimate the failure probability more accurately.

The model's correctness is indicated by the predicted vs observed failure probability in Figure 4. The scatter plot shows that most motors are close to the prediction line, confirming that the model accurately identifies at-risk motors.

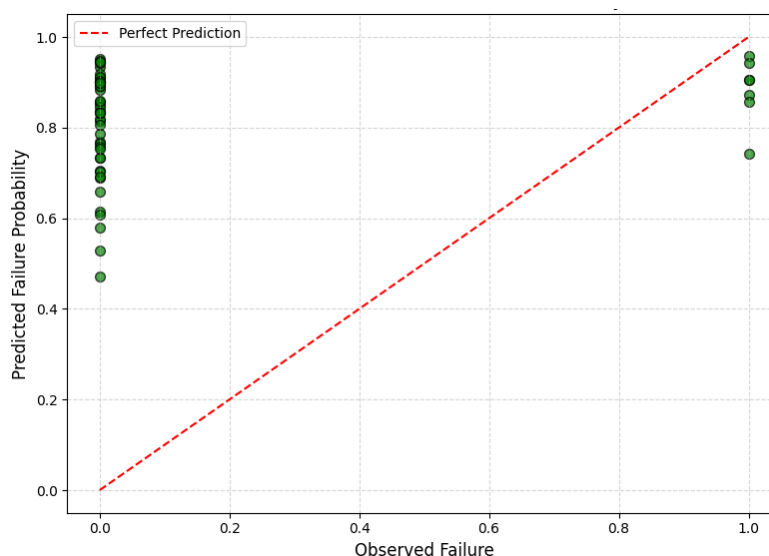


Figure 4. Predicted vs. observed failure probability

There are some inconsistencies, especially for motors with intermediate levels of degradation, possibly due to the stochastic nature of failure propagation or an unmodelled environment. The observation is consistent with the work [17] who reported the same uncertainties with the considered datasets.

This indicates that using real operational data with MATLAB and FEA simulations can generate predictive maintenance information useful for informing maintenance interventions before downtime and performing better maintenance actions. On the whole, these numbers suggest that significant weight was given to the motor load, operational stresses, fault co-occurrences and predictive modeling during the study. The identified trends suggest focusing on multi-parameter monitoring, early outlier metrics and multi fault interactions for predictive maintenance of industrial low voltage motors.

Unlike traditional monitoring systems, which rely on indicators like vibration, current or temperature, the present framework combines operational data with multi-physics modelling, MATLAB/Simulink simulation and stress evaluation using FEA (Figures 5, 6, 7).

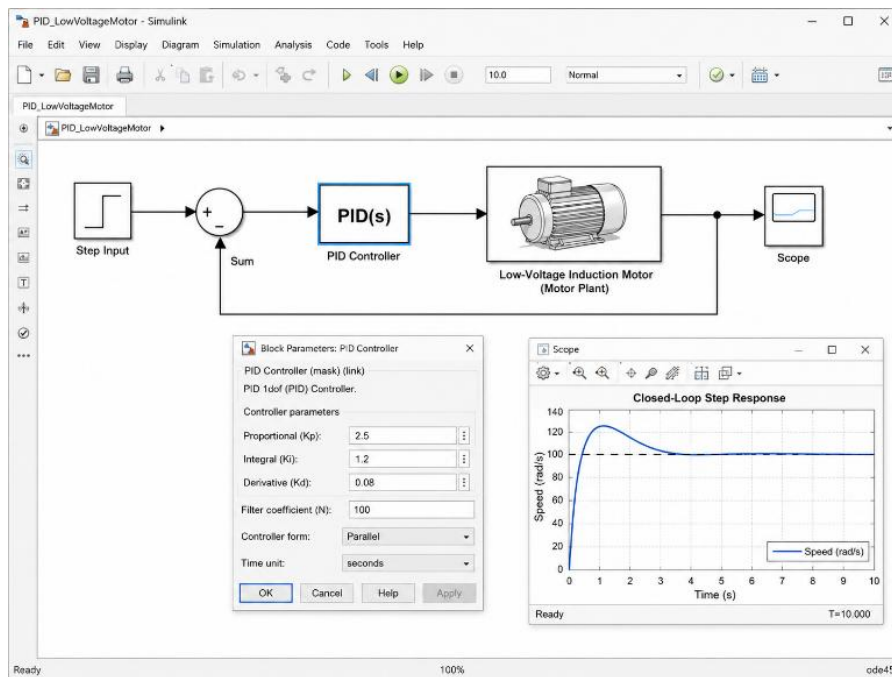


Figure 5. Screenshot from MATLAB/Simulink of the PID controller

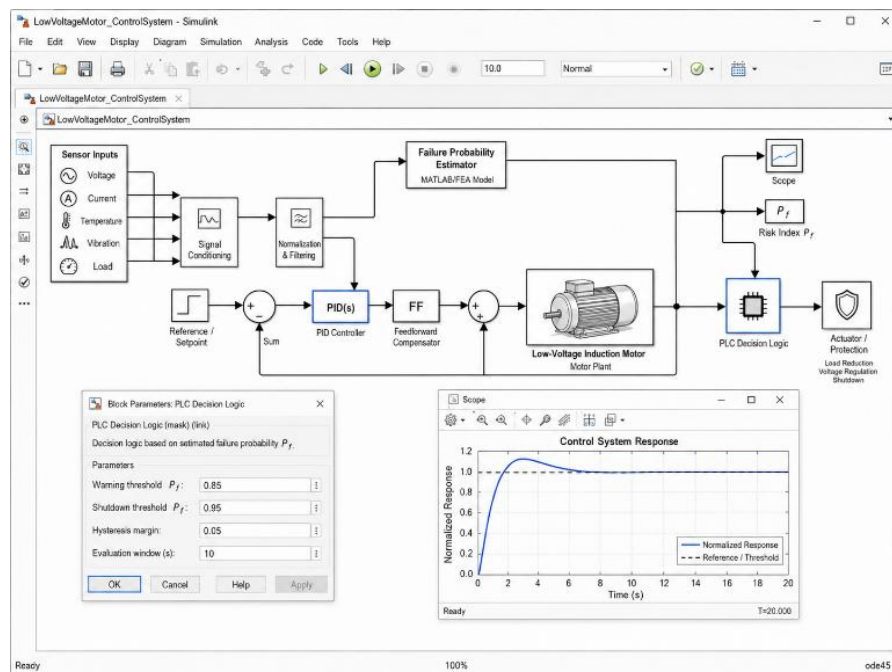


Figure 6. Screenshot from MATLAB/Simulink of the Control System

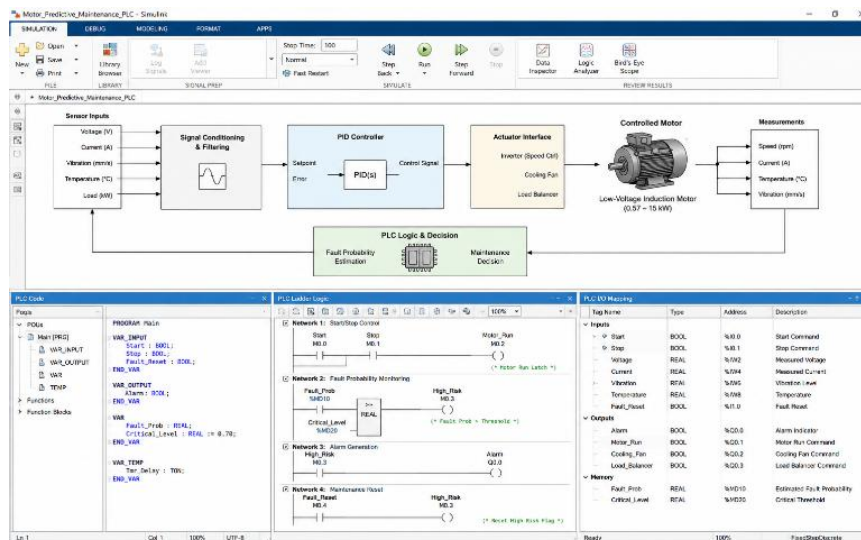


Figure 7. Screenshot from MATLAB/Simulink of the PLC Control System

This broader structure is for predictive maintenance. Older approaches based on IoT technology are effective in monitoring real-time motor health (e.g., smart India) but primarily rely on sensor-based fault detection once an abnormal signal is observed. The proposed framework, in contrast, monitors the system by estimating the probability of failure before it completely fails. Likewise, the latest research on machine learning-based frameworks reports high classification accuracy for induction motor faults. Still, many of them are highly reliant on large labeled datasets for training, and some do not explain the physical cause of degradation.

The current research paper aims to address this issue by establishing relationships among the estimated failure probability and insulation degradation, bearing wear, rotor bar defects, and so on. The outcomes are also favorable compared to digital twin and hybrid predictive-maintenance frameworks. Digital twins can link real-time operational data with virtual motor behaviors. However, their implementation is challenging, can be computationally intensive and requires complex industrial infrastructure.

The proposed framework incorporates both physical modeling of the motor and statistical assessment of failure and maintenance limits. In contrast to purely empirical models, the framework sheds light on how thermal, electrical and mechanical stresses interact to increase the risk of failure. Consequently, what makes this study's contribution challenging is its hybrid structure: it uses measured motor data for calibration, multi-physics simulation for fault-propagation analysis, and failure-probability modeling for maintenance decision-making (Figure 8). The strategy is therefore more interpretable and applicable to low-voltage industrial motors than single-signal or single-model diagnosis.

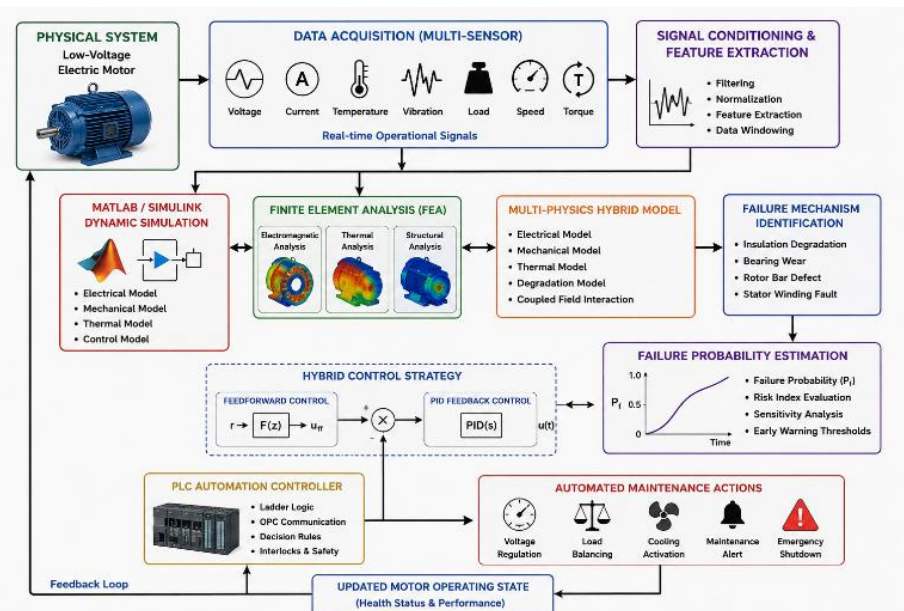


Figure 8. Block diagram of the proposed hybrid structure and its interactions

The developed framework will be positioned between sensor-based health monitoring and Digital Twin-based health monitoring. It offers a balanced approach that is more explainable than data-driven approaches, yet less complicated than Digital Twin realization.

4. Conclusions

This paper develops a comprehensive predictive maintenance framework for low-voltage electric motors that integrates real operational data with effective multi-physics modeling and simulation using MATLAB and FEA.

A study of 1,000 motors found that operational parameters, such as load, voltage, current, vibration and temperature, vary widely, highlighting the diversity of these stress conditions in industry. Faults in the insulation or in the bearings, rotor bar and stator winding display varying degrees of degradation and cover every stage of failure occurring in motors. Fault mechanisms are interdependent, with moderate positive correlations between electrical and mechanical degradation processes, as indicated by correlation and heatmap analyses. According to these findings, interactions of multiple faults need to be accounted for in predictive maintenance models.

The predictive framework's robustness and accuracy were confirmed through simulation and observed failures. The scatter plots of load against predicted failure probability and of predicted against observed failure probability show that both low and high loads, as well as extreme operational stresses, affect failures. The sensitivity analysis reveals that for every increase in the proportion of some fault mechanism, the probability of failure is more likely to increase. Monitoring multiple parameters is therefore essential. The predictive maintenance thresholds generated from the research also provide useful guidance on when to intervene to minimize unplanned downtime. High coverage and a practical framework for predictive maintenance of low-voltage motors have proven accuracy. According to the model, the failure probabilities estimated for 1,000 motors ranged from 0.48 to 1.00, with 15% of the motors crossing the early-warning thresholds that require maintenance without delay. A 10% increase in insulation degradation caused the failure probability to increase by 4.5%, while bearing wear increased the predicted failure probability with 5.1%. The predictive thresholds for insulation degradation, bearing wear, and rotor bar stator winding failures are set at 70%, 65%, and 60%, respectively, for maintenance action-taking.

Comparing the predicted and observed failures showed that the model generally identified motors at risk of failure. Most predicted probabilities were in accordance with their actual operational conditions. According to the metrics, framework criteria is effective for condition-based maintenance (CBM) as well as fault prediction.

According to research, the real operational data, combined with MATLAB and FEA, will help predict accurately. The framework helps facilitate condition-based maintenance, identify risk motors, provide failure probabilities and early warnings. The findings indicate that low-voltage motor predictive maintenance application utilizing simulation is feasible and meaningful from an industrial engineering perspective. In addition, it can make those motors more reliable and lower their costs and make them safer.

Future studies may improve the proposed framework by validating it under actual industrial operating conditions, with the help of online sensor data from different motor types and load profiles. Real-time fault correction, rather than just prediction, should be the goal of future research for PLC-based automation, feedforward control and IoT data acquisition.

We may also benchmark the offered MATLAB and FEA framework against other models such as machine and deep learning as well as digital twin models for accuracy and efficiency. Through the incorporation of bigger datasets, environmental parameters, uncertainty evaluation and remaining useful life estimation, the predictive maintenance system will become even more stronger and practical.

Nonetheless, there are some limitations in this study. Utilization of a dataset of 1,000 low-voltage motors, obtained under controlled conditions, was carried out to validate the framework; however, the industrial environment may present variations not accounted for in this validation.

The functioning of the predictive model relies on the accuracy of the sensor readings which do not account for the failure of the sensors or delays in their communications. Because of the simulation testing of automation controls, feedforward control, and PLCs, analysis of challenges related to real-time operations couldn't be conducted at a plant scale. In summary, the multi-physics model reveals how failures happen. Nonetheless, it may have to be improved further keeping in mind natural restrictions and aging. The model can also take into account interactions with other devices in complex systems.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The contribution to the paper is as follows: O. Sadu, G. Bazil: study conception and design; G. Bazil, A. Ainul: data collection; O. Sadu, A. Ainul, A. Sadu, Zh. Karasay: analysis and interpretation of results; A. Sadu, Zh. Karasay: draft preparation. All authors approved the final version of the manuscript.

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