



DATA-DRIVEN FAILURE PREDICTION AND CONDITION MONITORING OF THE A2 LOWER-ARM SERVO MOTOR IN A VERTICALLY ARTICULATED INDUSTRIAL ROBOT

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ABSTRACT

The growing demand for high precision and uninterrupted production in automotive manufacturing necessitates reliable failure prediction strategies for industrial robotic systems. In vertically articulated robots, the Axis-2 lower-arm servo motor is subjected to significant dynamic loading, thermal stress, and mechanical vibration, making it particularly vulnerable to premature degradation. Conventional control systems typically detect faults only after performance deterioration becomes critical, limiting opportunities for preventive intervention. This study proposes a multi-parameter condition monitoring framework for early failure prediction of the A2 lower-arm servo motor. Real-time measurements of motor current, surface temperature, and vibration velocity were acquired using externally mounted sensors under full-load operating conditions. Additional brake and resolver data were periodically evaluated to support system assessment. The collected operational dataset was analyzed using a Random Forest regression model to identify degradation patterns and estimate remaining service life. The results indicate that combined monitoring of electrical, thermal, and mechanical indicators enhances diagnostic reliability and enables early identification of abnormal operating trends. The proposed data-driven approach supports predictive maintenance planning, reduces unexpected downtime, and improves operational stability in industrial robotic applications.



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I. INTRODUCTION

This article provides an insight into how the failure in the lower arm of the Industrial Robot manipulator can be analyzed and predicted. The time saving benefits and high productivity, robotic welding has become important process in the metal and heavy industry. In the high-volume process undetected faults in the industrial robotic arms may be subjected to severe failures and losses, with the potential to lead to devastating results. The major and primary concern in these Industrial robotic manipulators is the impact on safety, where the automation line malfunctions and gives a significant risk to operators in the environment [1]. The impact of robot malfunctions may cause injury to the operator and even the machines in the working vicinity. The second most critical aspect affected by unpredicted problems is the quality of the produced parts [2]. The Robotic manipulators may continue to produce repetitive defective products, leading to significant rejections at the customer end and heavy financial burdens. This is the situation in which the Robot does not predict the end failure but slowly start degrading the quality of the end products before failure. Thus, to ensure the Robot safety, quality and high productivity of automated systems, the failure analysis and its prediction thus become very important [3].

Implementing real-time Analytics and visual systems that collect data from sensors mounted on Lower Arm Servo Motor and the robot controller. This data includes vibration values in mA or in mm/s, temperature readings in °C and motor current in Amps. Another relevant parameter includes resolver data and the motor brake data which is monitored manually at regular intervals and the values are noted [4]. Utilization of the advanced data processing techniques with the help of PLC and its output data on HMI dashboard to analyze the data collected by identifying anomalies along with deviations from pre-defined threshold conditions[5]. Development of algorithms based on data collected from sensors which is capable of accurately diagnosing the failure values of the detected faults. This model based on machine learning tool “Random Forest” and statistical analysis. The ML tool in python used for intelligent fault diagnosis, enabling the system to learn from past data and predict its failure over time [6]. Utilization of the ML data is used to predict potential faults before it occurs. This process also allows for planning for preventative maintenance, which minimizes the downtime and extends the lifespan of the Robot and its controller. It further becomes possible to implement the proactive failure-based maintenance, where maintenance schedules are based on the actual health of the Robot rather than conducting the activity at fixed intervals [7]. The Link Arm is the assembly located between the arm and the rotating column. It consists of linking arm body with the buffers.

The lower Arm Servo motor is directly attached to the Link Arm on which the Failure analysis is carried out [8]. The Speed of the Lower Arm is controlled by the servo motor depending on the cycle time requirement, component profile limitations and the component to torch weld angle of approx. 45°. With the advancement of time and the continuous motion of the robot, the servo motor is subjected to wear and tear. When a servo motor fault occurs, the robot’s Present Function shows errors such as mastering required (resolver error) in A2, motor overcurrent, excessive motor temperature, or collision detection in A2. In some cases, abnormal vibration may occur without any fault message being displayed [9]. The above faults in the Robot Lower arm do not give a prediction or a failure pattern by which the real time health can be monitored for the servo Motor. To further analyze the faults and collect the data in real time monitoring a test equipment proposed which is mounted with the sensors on the servo motor. The sensor’s output values are monitored in real time and the data collected from these sensors are analyzed with statistical tools. The output values are compared with the threshold values, and the failure trend is calculated with help of Random Forest ML tool [10]. The Servo Motor mounted on each axis of 6 DOF manipulator has three major parts, The Robot, Brake and the Feedback mechanism for the positional accuracy and repeatability in the Robot. The encoder or the resolver sends continuous data to the drive related to its actual position in the working envelope of the Robot.

II. METHODOLOGY

The stator generates a rotating magnetic field based on the rotor’s position, enabling efficient torque production. Current flows through the windings to create this magnetic field, and its magnitude changes according to the torque demand. Smooth rotation of the rotor is supported by ball bearings that minimize friction and ensure stable movement [11]. The shaft transmits the mechanical output power of the motor to the load through a transfer mechanism such as a coupling. The rotor, typically fitted with high-performance rare-earth or other permanent magnets, is mounted externally on the shaft [12]. An optical encoder continuously tracks the shaft’s rotational speed and position to provide accurate feedback. Communication between the encoder (or resolver) and the robot control system is carried through the encoder cable, while the motor cable connects the brake and supplies three-phase electrical power to the motor shown in Table 1.

Table 1: Lower Arm Servo Motor Specification.

SI No	Attributes	Value
1	Rated Output	2 KW
2	Rated/Max Speed	3000/5000 r/min
3	Rated torque	6.4 Nm
4	input	3 ϕ AC 210 Volts 12.3 Amps
5	Ambient Temperature	40°

Source: Authors, (2026).

II.1 TEMPERATURE IMPACT ON HIGH-SPEED ROBOT MOTION ON LOWER ARM SERVO MOTOR:

The predominant cause of servo motor failure is overheating. To avoid electrical interference caused by conduction in nearby motor windings, good winding insulation is essential in servo motors. Another way to prevent short circuits is by separating the phases [13]. Insulation acts as a thermal barrier, allowing the motor to maintain its optimal working temperatures. Insulation also provides structural support, which lessens the likelihood of physical damage to the winding, in addition to the benefits already mentioned. The servo motor’s thick insulation is designed with a margin of safety that has an integrity against breakdown that is far higher than the permissible voltage [14]. This technique to winding insulation in motors incorporates a multi-layered arrangement of coils and slots. The servo motor winding’s Class F insulation has an operating temperature rating of 155 °C, with an ambient temperature of 40 °C. The insulation of servo motor windings is classified into categories. The National Electrical Manufacturers Association (NEMA) specifies working temperatures for each insulation class, as illustrated in Table 2. The temperatures are determined by the operational load of the robot under load conditions. The current increase in the lower arm robot servo motor is attributed to the overheating of the stator windings and the absorbed leakage current. Insulation breakdown creates aberrant pathways that facilitate the flow of leakage currents. Thermal, electrical, environmental, and mechanical stressors on the insulation material will induce the formation of leaky current pathways within the winding insulation. The severity of insulation deterioration is an accurate estimate of the size of leakage current in the anomalous path. Accurately identifying the origin of the leakage current within the winding insulation is frequently challenging. The resultant leakage current is attributable to capacitive and resistive leakage currents, as illustrated in the equation below.

$$i_t = i_r + i_c \quad (1)$$

The capacitive leakage current, i_c , arises from alternating current traversing between conductors that are insulated by a dielectric material. Resistive leakage current, i_r , arises from current loss through the insulation around the conductor. Resistive and capacitive leakage currents are contingent upon the supply voltage. The integrity of the insulation material is solely determined by the size of the resistive leakage current. The degradation of insulating resistance is exacerbated by increasing levels of resistive leakage current [15]. The leakage current is directly proportional to the surface impurities on the insulator; thus, an increase in contaminant deposits results in a greater flow of leakage current. For example, water accumulation behind a layer of pollutants results in a reduction of the insulating surface resistance. Preventative maintenance must be conducted if the leakage current values remain unchanged over time. To analyze the increase of temperature separately on the motor with time, NTC type temperature sensor probe is mounted on the motor surface, and its controller is located at a distance so as not to hinder the robot motion. The temperature is recorded at regular intervals with robots in full load running condition. When the Robot starts the Servo motor is observed at ambient temperature. Withing an hour of full operation the temperature reaches around 36 degrees as per the 10-hour data observed. There is no major escalation in the temperature observed after one hour of robot operation as seen Figure 1.

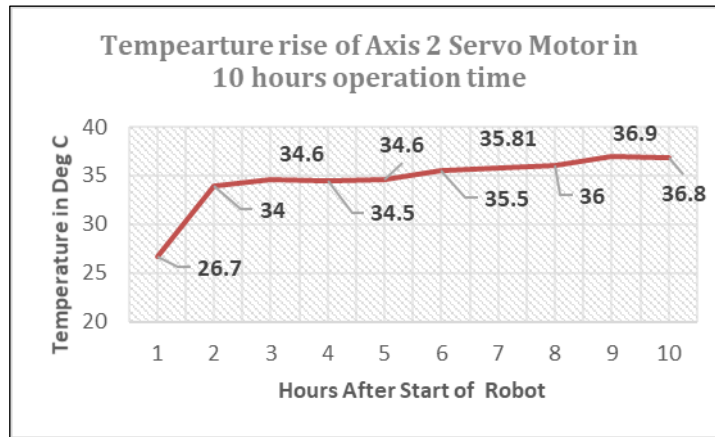


Figure 1: temperature of Robot lower arm servo motor in ambient Running condition.
Source: Authors, (2026).

The temperature of the lower arm servo motor of the robot is raised over a period in constant operation and it's a function of its thermal time constantly and is generally characterized by its compatibility to fit in the robot and how its designed to get cooled under running condition. With the rise in temperature the resistance of the motor winding also increases linearly with gradual rise in temperature as per the following mathematical relation.

$$R(T) = R(T_0)[1 + 0.00393(T - T_0)] \quad (2)$$

Where T is the winding temperature ($^{\circ}\text{C}$), T_0 is the ambient reference temperature which is considered as 25°C , 0.00393 being the temperature coefficient for copper. (in case of Aluminium winding this value is changed to 0.00403). The temperature rise of the motor over long period of time when it draws overload current is still defined as function of time as

$$T(t) = T_{\text{ultimate}} - (T_{\text{ultimate}} - T_{\text{ambient}})e^{(-t/\tau_{\text{thermal}})} \quad (3)$$

$T(t)$ is temperature with time t , T_{ultimate} is the final temperature or peak temperature under the robot load condition and T_{ambient} is ambient temperature or the temperature of the motor at the start of the Robot along with τ_{thermal} being the thermal time constant. The ultimate temperature is mostly achieved at 5 times the thermal time constant.

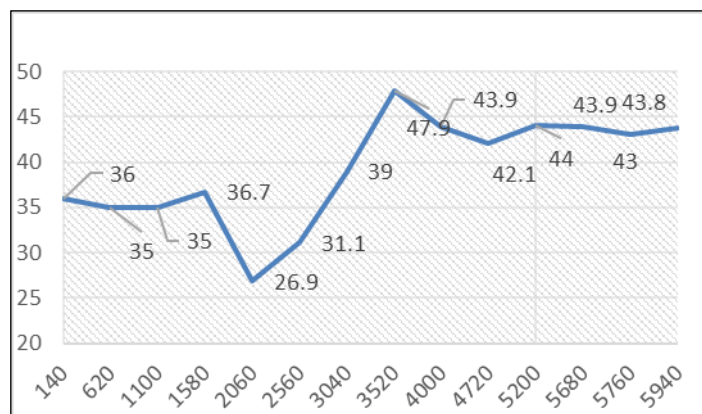


Figure 2: temperature rise of the servo motor with increasing servo operational hours.
Source: Authors, (2026).

The data collected for temperature variants in the servo motor at regular intervals and not exceeding 6000 servo hours depicted that the ambient temperature escalation in the servo motor because of operational factors gave a rise of approx. 13 degrees compared to normal operating temperature of 36 degrees, which rise to an ambient temperature of 43.8 degrees as shown Figure 2. This temperature is however normal operating temperature and motor functions perfectly at this rise. It has also been observed that the temperature rise is steep during the summer operating conditions which goes to 47.9 degrees, motors still observed to work perfectly without any failure in this condition [16]. This ambient temperature because of environmental temperature gives rise to the working temperature in the surroundings and the complete robot temperature seems to rise in this environment. This spike in temperature is generally ignored for the analysis and the final and end temperature only considered.

II.2 CURRENT IMPACT ON HIGH-SPEED ROBOT MOTION ON LOWER ARM SERVO MOTOR:

Consequently, it is essential to assess the temporal flow of these currents utilising past data to evaluate the condition of the servo motor. Motor current monitoring can be achieved by measuring the current consumption during operation by the integration of a current transformer with the controller, as seen in Fig 7. The limitations of this approach, based on real-time current data, involve extensive computations, whereas wavelet and Fourier transformations are only effective for steady-state diagnostics. Recently, numerous machine learning and artificial intelligence methodologies have been established for categorisation and prediction challenges [17]. Neural networks, support vector machines (SVMs), K-nearest neighbours, and long short-term memory (LSTM) deep learning have become prominent in anomaly identification. The drive in the robot controller continuously monitors the rise in current within the stator windings. It is essential to meticulously select its settings and those of the optimisation methods. The classification of leakage currents between phases and phase-to-neutral using deep learning is analysed based on the output provided by the current transformer (CT). This CT is affixed to the phase wires that terminate prior to the Robot drive controller. The mathematical relationship between rated power of the servo motor (P_{in}) relates current (I in Amps) and voltage V in volts). In Robot axis the servo Motors gives some losses which must be considered as efficiency (η) and power factor ($\cos \phi$). The name plate of the servo motor mounted on the Robot (power) is its mechanical output power P_{out} of 2.2 kW.

$$\text{Rated input power } P_{in} = P_{out} / \eta V \quad (4)$$

For 3 phase AC servo Motor on the Robot Arm, we can infer the following mathematical relation

$$P_{in} = \sqrt{3} * V * I * \cos \phi \quad (5)$$

$$\text{or } I = P_{in} / \sqrt{3} * V * \cos \phi \quad (6)$$

combining both equations, we get

$$P_{in} = P_{out} / \eta \sqrt{3} * V * \cos \phi \quad (7)$$

Considering the fixed input 3 phase voltage of 415 volts, and efficiency being 0.85 and power factor being 0.80, the motor approximately consumes 4-5 Amps. At the start of the Robot, motor tends to draw more current to overcome the inertia factor but gets stable and runs at nominal current. Initially the motor may draw 9-10 Amps current for few seconds but goes back to normal of 4 Amps approx. during operation. After a prolonged period of time the Motor tends to draw more current considering several factors of overheating, irregular power supplies and frequencies, excessive movement, wear and tear of the bearings, weakening of the insulation winding, short circuit etc. the present servo motors are protected against the damage during high peak loads for few seconds, but is not consistent [18]. Before failure the Motor will tend to draw much higher current ranging from 8 Amps to 20 Amps. Peak Servo current (during failure) causes the motor to draw maximum peak torque ranging from 200% to much higher value. The rated rpm being 3000 rpm at max torque value of 7.0 N-m. This torque value increases exponentially before permanent failure. It has been considered that during normal peak load of the Robot in the running condition the motor may draw current to extent of 110-15 Amps for 2-3 seconds max. Robotic AC servo motors are engineered for rapid acceleration and deceleration and heavy spikes in short term load when the robots are subjected to external forces such as collision with fixture during motion. The current for 3 phase AC servo motor mounted on Lower arm of the Robot is measured with help of KRYKARD power analyzer ALM 31, which has measured $A1_{rms}$, $A2_{rms}$, $A3_{rms}$ and AN_{rms} on regular time intervals to check the current pattern drawn by the robot Motor in full running load conditions. A Sinusoidal current wave is represented by the mathematical relation.

$$i(t) = I_{peak} \sin(\omega t) \quad (8)$$

$$I_{rms} = I_{peak} / \sqrt{2} \quad (9)$$

From the other readings from the Power analyser for the current values, only the RMS values are considered for the research analysis. The Peak values are not relevant for the data collection, hence for the half wave rectified signal considering zero value at the other half the RMS values of current drawn is recorded to predict the abnormalities and failure in the Motor over a long period of time.

II.3 EXPERIMENTAL SETUP

Figure 3 presents the original three-phase power distribution inside the robot controller before instrumentation, highlighting the absence of dedicated real-time current monitoring at the motor level.

This baseline configuration justified the integration of additional diagnostic elements. Figure 4 demonstrates the installation of current transformers on the R, Y, and B phase conductors, enabling non-intrusive measurement of phase-wise RMS current under actual operating conditions. This arrangement supports detection of overload, imbalance, and abnormal torque demand without disturbing normal robot functioning. Figure 5 illustrates the combined mounting of vibration and temperature sensors on the servo motor housing, establishing a multi-parameter condition monitoring framework. The synchronized acquisition of thermal, mechanical, and electrical data strengthens failure prediction reliability. Figures 6 and 7 present RMS current trends using narrow and broad sampling intervals, respectively. The short-interval data captures transient spikes during dynamic motion, while the long-duration plot reveals overall stability around nominal current values with occasional deviations. Together, these observations confirm stable operation within monitored hours while emphasizing the importance of continuous trend evaluation for predictive maintenance planning. The amount of current drawn by the robot Servo Motor for approx. period of six thousand servo hours analysed and was noted that the spike of maximum value of 4.69 Amps observed for single time followed by next lower values of 4.4 Amps and 3.77 Amps respectively. A trend could not be established for the current to increase over a period. The mean value of the current drawn by second axis of robot found to be. 3 Amps. The tendency for the motor to fail will draw more current at early intervals to the extent of 6 Amps or 7 Amps, at current value higher than that of 7 Amps, the Motor may get heated up and fail before time.

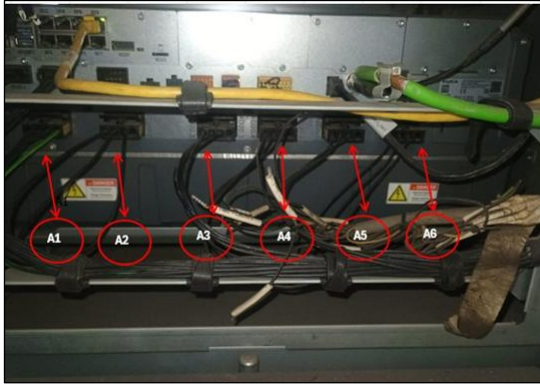


Figure 3: Robot Controller KRC5 (A1-A6) Servo Motor inbuilt power connections before CT installation in Axis 2 Motor.

Source: Authors, (2026).



Figure 4: Installation of the CT at Axis 2 Motor of Robot in R, Y and B Phase Wires.

Source: Authors, (2026).

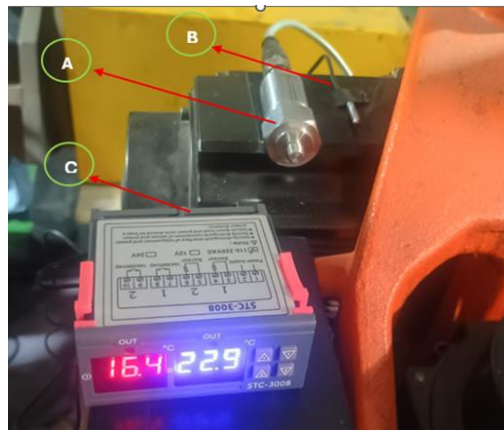


Figure 5: Experimental setup of temperature Probe and Vibration sensor on the Robot Servo Motor-A2 Axis, (A-Vibration Sensor, B-NTC type temperature probe, C-Temperature Controller).

Source: Authors, (2026).

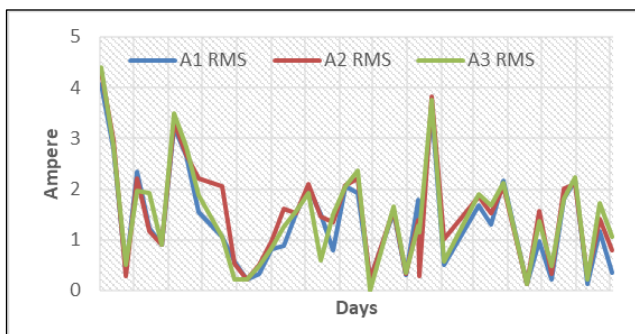


Figure 6: "Plot for motor RMS current value against time to analyse run-to-failure data- narrow interval.

Source: Authors, (2026).

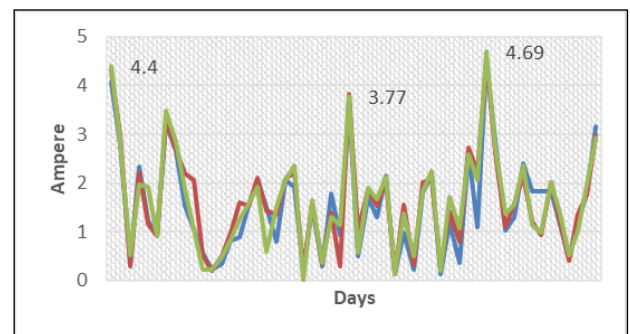


Figure 7: "Plot for motor RMS current value against time" to analyse run-to-failure data - broad interval.

Source: Authors, (2026).

II.4 VIBRATION IMPACT ON HIGH-SPEED ROBOT MOTION ON LOWER ARM SERVO MOTOR:

Robotic manipulator and the complete cell System performance is mostly dependent on the impact of vibration and temperature data as observed on the total operating time of the system, operating conditions of the system, and the external environment. So, the reference value can be obtained from Robot which is in actual running condition. The vibration is monitored during the Robot operation in actual welding process. The critical levels need to be determined under Robot. The P&F make vibration sensor is used to monitor and detecting errors which allows it to generate error when the set limit values exceed as compared to the optimal values [19]. Vibration values measured at measured for Tamagawa TBL-I III series motor or 389683 Robot Lower Arm AC servo motor at running RPM speeds. The working time for all the measurements will be more than 5,000 operating hours or Robot in Servo ON condition. The vibration values increase with the increased number of Servo Motor rotations as an usual phenomenon. After examination of the data, it was observed that no abnormal values observed for initial servo operational hours, and the servo motor continues to operate in regular operations as per the pre-defined robot speed. Additionally, when the heat has been measured, the reference value of 35°C was found to deviate to minor deviations. The max RPM of lower arm AC Servo Motor considered is 3000. The validation of the results of measurement made with max 3000–0 RPM cycles in the Servo Motor, considering the maximum speed of the Robot of 1.5 m/s-0 m/s. The Abnormal vibration in the Servo motor specially in the lower arm of the robot has degradation impact on the overall process [20]. There is precision loss in the Servo motor which loses its encoder or resolver's ability to hold the exact position and give its position feedback to the controller. It reduces the accuracy task in the process of GMAW where in the tolerance of deviation is maximum of $\pm 0/5 \times (\text{Wire diameter})$. Mechanical wear of the lower arm Servo Motor are subjected to excessive load and heat which generates frequent maintenance requirement. The excessive vibration if beyond 2.5 mm/sec for a very long period of time also generates the increase in the winding temperature. This gives random fault to the electronic components and problem of motor overheat encoder error or major electronic failures also occurs.

A running Robot system operates between 200 mm/s to 1.2 m/s. this operating range in the robots generally exceeds the limit of the values of the vibration after prolonged servo operational hours. The vibration level observed at high running speed of the Robot depicts that the value randomly exceeds over the vibration limits, the external factors beyond the robot system may be ignored like , movement of trolley near the robot or the strokes of the Press shop. The rise in these vibration values to be seen by the Vibration sensor data between the measurements of high-speed motion in the robot manipulator. Similar impact is not confirmed to repeat in the repetitive research study. This spike was observed in both measurements made with 0-1.4 m/s and different frequencies in data to be observed. with these vibration values, the motor's temperature readings and monitoring is carried out separately with the mounting of temperature controllers on its surface. The prediction of temperate impact on the servo motor is analysed separately. First the data is captured on single robot and then the similar data is being captured on 15 robots simultaneously for all the robots. Vibration Sensor VIM32PL-E1V16-0RE-I420V14 mounted on the surface of the servo motor of the lower arm and the data then captured with this sensor in the robot running condition. The robot runs with the predefined speed set with the components. Vibration of the lower arm robot servo motor measures in terms of velocity which ranges between 0-16 mm/s (Vrms) with an accuracy of ± 0.1 mm/s. the sensor gives analog output to PLC as current output of the vibration variable (4mA to 20mA), meaning that zero vibration corresponds to 4mA and vibration of 16 mm/sec corresponds to 20mA. The motor fails at vibration value of 4.0 mm/sec and is considered as threshold failure value. The failure trend can be observed for the values received from the vibration sensor, and the progressive increase in vibration amplitude over servo operational hours is illustrated in Figure 8. It has been considered that the Robot Runs 20 hours a day and the vibration values have been noted at interval of every 20 hours. The failure trend can be observed for the values received form the vibration sensor. The threshold value near to 4 mm/s over a period tends to fail. For ease of calculation the current values in mA obtained from Senso PLC integration has been converted to vibration with the above equations [21]. Since the current and the vibration values are linearly corelated with a difference of 4 as per the following Table 2.

Table 2: current output can directly be scaled Vibration (mm/S) =Current (mA)-4.

Sl No	Vibration (mm/s)	Current (mA)
1	0	4
2	4	8
3	8	12
4	12	16
5	16	20

Source: Authors, (2026).

With the observed trend and statistical value, the failure of the motor predicted to fail near to 24000 servo operations hours. Preventive measure and predictive maintenance must follow near to 18000 hours. the standard periodic maintenance procedures do not predict the failure of the robot.

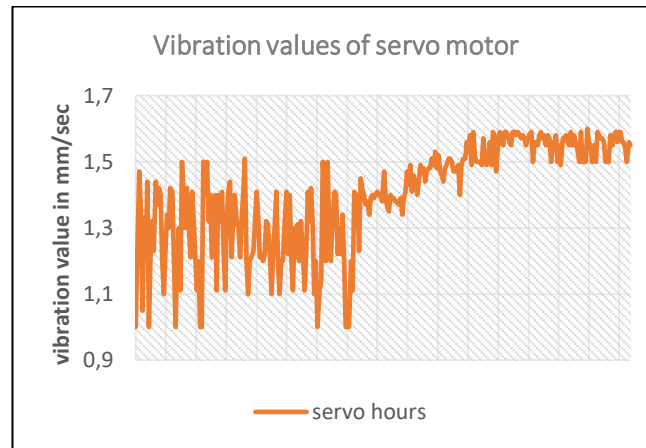


Figure 8: Increased Vibration values of the Servo Motor compared with Robot running hours.
Source: Authors, (2026).

II.5 OPTIMIZATION OF RANDOM FOREST REGRESSION

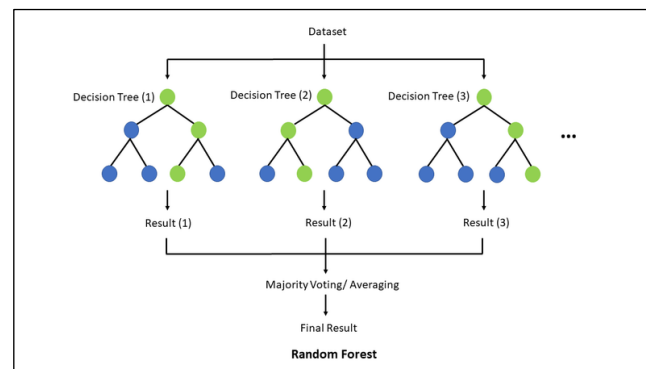


Figure 9: Random Forest regression Structure.
Source: Authors, (2026).

A random forest is a traditional machine learning technique that amalgamates predictions from various decision trees to generate precise and consistent outcomes. It is utilised for classification and regression problems. For the regression job, we employed the Random Forest Regression approach to predict numerical values. It forecasts continuous values by aggregating the outcomes of several decision trees. Figure 9 illustrates that Random Forest regression is a machine learning technique employed for forecasting and addressing regression issues, particularly utilising decision trees to forecast failures and the mean of failure predictions. A Random forest regression uses several decision trees to collect the data and use its average to calculate the final prediction. The random forest regression has following important parts are Bootstrap Sampling, Decision Tree construction and Integration of Predictions [22]. The decision tree regression in the machine learning process starts by checking the current drawn by the robot servo motor followed by branches of temperature and then vibration impact as shown in Figure 10. Each path selected by the decision tree leads to failure prediction of low, medium and high categories.

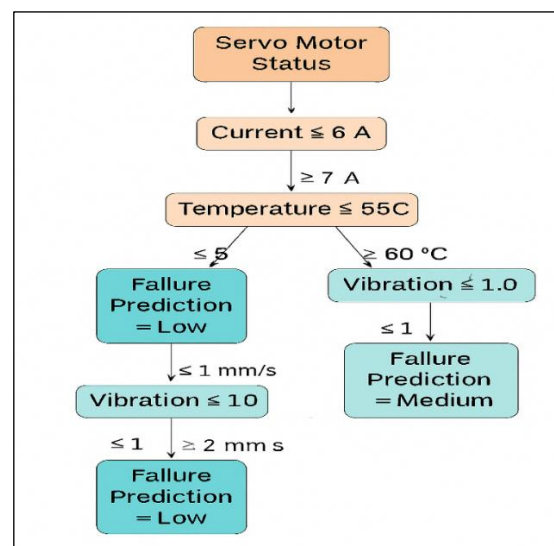


Figure 10: Proposed Failure Prediction model workflow in Random Forest Regression method.
Source: Authors, (2026).

The failure features of current, temperature and vibration contribution to the failure weightage as per the data is represented as Figure 11. It is observed from the data that the temperature contribution towards the failure of the Robot servo motor contributes most as compared to the other observed parameters. However, the abnormal vibration and the increase in the current drawn by the servo motor contribute to the major failure, temperature increase in the motor while continuous operation is key concern.

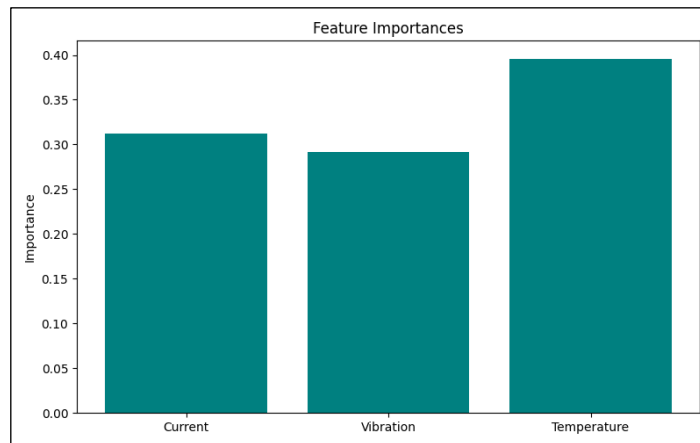


Figure 11: Failure Feature importance as judged by the ML tool.
Source: Authors, (2026).

III.RESULTS AND DISCUSSIONS

Since it is challenging to measure the lower Arm of Manipulator Servo motor temperature, vibrations and, and increasing currents before failure in practical applications, a well-trained prediction model can further be used to eliminate practical measurement devices. The effects of temperatures and leakage currents on insulation winding have been discussed, and their trends can be utilized to inform on insulation integrity over time [23]. In our present research carried out, the performance of random forest regression using python coding and predicting the failure of the servo motor has yielded ad mixed result .The historical data collected for monitoring the overall robot health and specially the servo motor of the lower arm health monitoring using temperature sensor, power analyzer, and vibration sensor were acquired from its real time output. The data were then preprocessed according to the requirements of the utilized estimation algorithm directly in the machine learning tool using python. Failure prediction by the Random Forest Regression has also used historical data by the sensor as an input and with ML internal processing with the following steps. Importing necessary library in python, Data loading and inspection, Data Processing and learning based on the inputs given, Plotting of the data and Execution and data saving.

III.1 TEMPERATURE FAILURE PREDICTION

The blue line on the Figure 12 represents the temperature profile recorded periodically across a period of 0 -6000 servo hours. The prediction tool assumed threshold value of failure at 45 degrees. Red points are the points where temperature exceeds the threshold value above 45 degrees and are flagged as potential failure points [24]. We conclude that the Robot Servo motor temperature remains at a stable phase during the interval of 0-3000 servo hours, 45 degrees temperature is the ambient temperature reached during peak summer temp and needs to be ignored. The motor reaches the critical phase ranging from 3300-3600 servo hours in which the temperature tends to peak near 50 degrees. At range of around 4300 to 4600 servo hours the Robot servo motor temperature remains in chronic monitoring at temp of around 46 degrees. Beyond 5000 servo hours temperature stabilizes around 40 degrees but remains at stress level because the insulation windings have been subjected to higher temperature over a prolonged time. Thus, regular and supervised inspection is needed between 3300 -4300 servo hours and arrangements required for lowering the ambient temperature, gear box lubrication and reduced robotic load if feasible (allowing time or no-load time as a planned regular activity in this interval). The threshold of 60 degrees is reached around 14000 servo hours. An early warning of motor failure due to increase in temperature may be predicted around 13500 servo hours if the robot runs 20 hours a day. Critical monitoring required once the temp goes beyond 50 degrees.

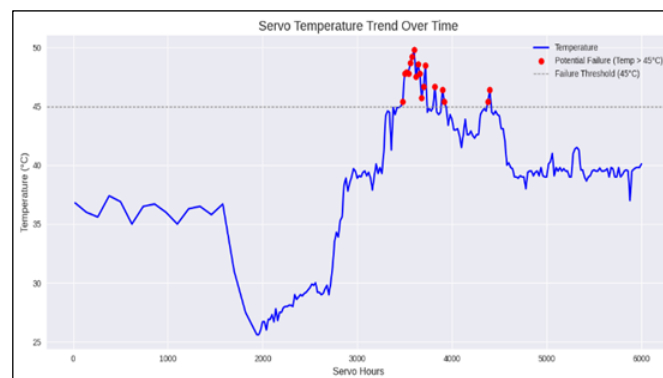


Figure 12: Servo Motor Temperature Failure prediction.
Source: Authors, (2026).

III.2 VIBRATION FAILURE PREDICTION

The vibration values generated over the operating hours of the robot, along with the predicted failure points above 1.5 mm/sec, are presented in Figure 13. The vibration values observed is higher if compared to the values of the Robot motor during installation. Over operating period of robot servo hours the values of vibration observed to reach higher value, which is still considered to be in normal working condition.

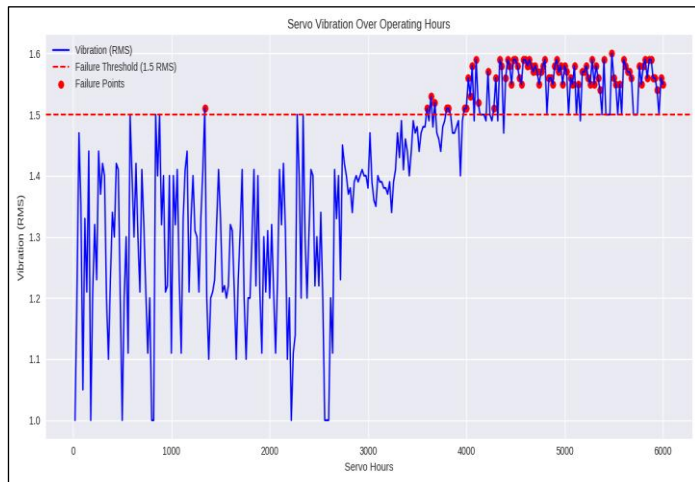


Figure 13: Servo Motor Vibration failure prediction.
Source: Authors, (2026).

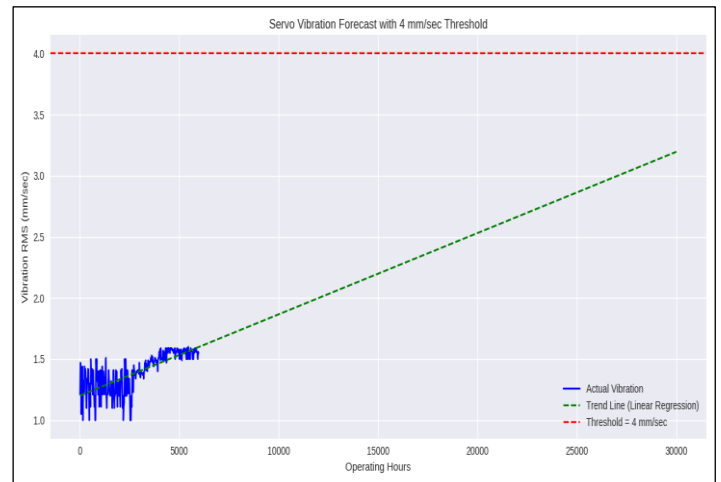


Figure 14: Vibration failure prediction with trendline.
Source: Authors, (2026).

During the initial working hours of the robot up to 200 servo hours, we can see the motors were in healthy operating condition [25]. If the vibration values observed is above 1.5 mm/sec, the trend can be established that there is a gradual increase in vibration of the servo motor, and it tends to reach the stage of the early wear. Since the threshold value is expected to be approx. 4 mm/sec as the cause of failure, the motors are required to be checked at regular intervals to avoid the high risk of bearing or alignment failure. The servo motor of the Lower arm gives output power to the harmonic gear box which as predefined reduction gear ratio of approx. 50:1 maintaining necessary torque and maintaining high precision. A cross check and preventive maintenance of the robot is thus necessary to visualize the mechanical condition at every 4000 servo hours. The regression trendline as observed extended with the green line in Figure 14 predicts that the servo motor will reach to the vibration value of 4 mm/sec at approx. 30,000 servo operating hours of the robot. The growth of the trend is however slow in the observed range, but the wear of the motor generally accelerate in a nonlinear manner. The failure of motor considering other factors like damage and collision can result in unexpected vibration values and may be subjected to premature failure. After the Servo motor tends to vibrate at approx. 2 mm/sec after 15,000 servo operational hours it must be planned for predictive failure and following the trend, a wait till the motor reaches value of 4 mm/sec must not be considered. Operational adjustments and deeper diagnosis like, encoder check, robot other axis vibration check, robot grouting on the foundation bolts must all be checked so that the possibility of secondary reason for the motor to increase in the vibration values is eliminated. The prediction for the motor to fail is at approx. 25,000 servo hours, it may fail near to this value in both before and after condition [26].

III.3 CURRENT FAILURE PREDICTION:

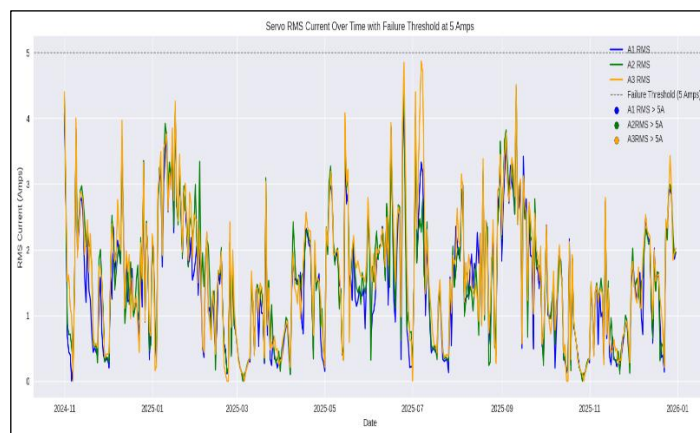


Figure 15: Current failure prediction in servo Motor.
Source: Authors, (2026).

The current trend analysis of the lower arm servo motor shows variations in RMS values recorded over periodic intervals. The prediction output of the Random Forest regression model, highlighting warning and critical zones, is presented in Figure 15. The results indicate that average RMS current values remain near nominal levels, with occasional spikes reaching 3.5–5 Amps during high load conditions.

If the motor starts drawing more current, it gets heated up rapidly at nominal RPM causing the motor winding and encoder to be overheated and get prone to the failure [27]. The result shows the average RMS value on monthly intervals and in a few instances increasing to value of 3.5 Amps and towards critical value of 4.5-5 Amps. If the value drops to zero it may also be a sign of short circuits but is not considered in this study and the result arising from the purpose is also not a part of the research. Result of Current values of A1, A2, A3 phase observed at Robot full load condition periodically and cluster of spikes in the RMS values were observed during period of June-Sep in which the current RMS value spiked beyond 3.5 Amps meaning a strong percussion for approaching towards the failure trend. Current drawn by the Lower arm servo motor beyond 4 Amps not considered to be normal and even the current spike for short period of time may damage the Servo Drive electronic components [28]. A systemic risk was also observed in the month of Sep when all 3 phase spiked above 4.4 Amps. Several instances are also observed when the motor current trends to draw almost zero current. in this situation also there is a chance for the motor winding to fail. If the Motor draws nearly zero current in full load condition, then there are chances of abnormality either in the Motor side or at the servo drive end which is controlling the dynamic torque of the motor in the running condition [29]. The Motor, however, is in normal running condition and no signs of abnormality in the Robot performance is observed, meaning that current spikes near to 4 Amps are at high load but not critical. The motor does not tend to fail immediately. Current range from 3.5 to 4.8 Amps are in warning zone rather than motor moving to immediate failure.

III.4 LEAKAGE CURRENT ESTIMATION IN THE EXISTING SYSTEM

The effects of leakage current in the Servo Motor could not be clearly established in this study. The leakage current generated is neutralized through proper robot body earthing. The grounding loop between the robot, controller, and earth pit ensures that when the resistance value remains below 2 Ohms, leakage current does not significantly influence motor failure or the developed prediction algorithm. The summarized observations of current-based failure prediction are presented in Table 3.

Table 3: Current failure prediction Summary.

Sl.No	Month	Threshold breach	Failure event
1	Nov-24	Critical	Partial (A1=0, A3=0)
2	Dec-24	Warning	none
3	Jan-25	Critical	none
4	Feb-25	Warning	partial(A3=0)
5	Mar-25	none	Partial (A1=0, A3=0)
6	Jun-25	Critical	none
7	Jul-25	critical	none
8	Sep-25	critical	none
9	Oct-25	none	partial (A2=0,A3=0)
10	Nov-Dec-25	moderate	none

Source: Authors, (2026).

IV.CONCLUSIONS

This study investigated the degradation behavior and failure prediction of the lower-arm servo motor operating under full-load industrial robotic conditions. The analysis identified temperature rise, RMS current variation, and vibration growth as the primary indicators influencing motor health, while additional factors such as brake degradation and resolver malfunction may further contribute to performance deterioration. A multi-sensor monitoring framework was implemented by integrating temperature probes, current transformers, and vibration sensors directly onto the operating robot. The acquired real-time data were processed using a Random Forest regression model developed in Python to estimate failure trends over extended servo operating hours. Although modeling motor failure in dynamic robotic environments is inherently complex due to interacting thermal, mechanical, and electrical factors, the proposed approach demonstrated the capability to detect abnormal patterns and predict potential failure windows with reasonable accuracy. The results confirm that progressive increases in temperature, sustained current deviations, and rising vibration levels can serve as early warning indicators for preventive maintenance planning. The developed methodology reduces reliance on fixed maintenance schedules and supports condition-based decision making. Overall, the integration of sensor-driven monitoring with machine learning-based prediction provides a practical and scalable framework for enhancing reliability and extending the operational life of industrial robotic servo systems.

V. AUTHOR'S CONTRIBUTION

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