An integrated Prognostics Driven framework for Defect, and Health analysis in Industrial Motors

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Abstract. The fourth industrial revolution in today's world has changed advanced manufacturing. Its fundamental process such as machining, welding, and additive manufacturing (AM) are altered by synthesis of artificial intelligence (AI) and machine learning (ML). The quality control (QC) for product, focusing on part-level defect detection, and "Predictive maintenance" (PdM), focusing on asset-level health of machines are often treated as distinct functional challenges. With the help of integration framework between predictive maintenance and industry 4.0 technology, Industries are benefited with improving the operational efficiency, shorter production time and optimized resources.
In this research study, A predictive maintenance framework has been developed for a coolant supply motor during its useful life to accurately detect early defects and predict remaining useful life to prevent unscheduled downtime and condition-based maintenance. The machine learning model employs a dual modal approach using a support vector machine (SVM) for boundary-based classification and a random forest (RF) for ensemble-based fault detection. It can be concluded that study will be beneficial to the industry professionals to provides a holistic solution for anomaly detection and remaining useful life estimation.

Keywords: Prognostics and Health Management (PHM), Machine learning, Predictive Maintenance (PdM), Fault Detection, Induction Motor.

1. Introduction

The manufacturing industries are upgrading themselves to stay in the competitive environment to achieve higher operational efficiency, greater product quality, and improved production time. For this, industries are using many tools and techniques in different areas of operations. Maintenance of machine components are essentials to maintain the machines in operational condition. Earlier, industries depend on schedule and preventive maintenance. These maintenance strategies help industries to some extent but have some limitation or results in unnecessary servicing and late detection of faults. Machine's real time health is a significant concern for industries and modern

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solutions such as predictive maintenance has potential for their longer life. Predictive maintenance is a broader term in aspects of implementation, as the input can be in the form of maintenance records, threshold values of concerned parameters or healthy to failure data. Inferences that help to predict machine health can be obtained from techniques like remaining useful life. Use of diagnostic algorithm over sensor data for predicting the defects or breakdown helps to schedule maintenance for optimizing resources like time, money, etc [1]. This concept of predictive maintenance is a subset of Industry 4.0, which integrates cloud service, Artificial Intelligence (AI), cyber-physical systems and internet of things [2]. A key aspect on which the implementation of predictive maintenance is based is data. The data requirements for developing a prognostic model are based on various requirements; some classical categories of data are maintenance records, threshold data, and healthy-to-failure state data. Smart sensors used in industries are also a necessary input for fault detection, and the availability of all data makes predictive maintenance an effective option [3]. Use of the induction motors in industries is extensive, i.e. manufacturing, power plants, transportation, and process industries. Motors also contribute as a foundation base of power plants and transportation industries. Any contingencies in their functioning during operation can lead to severe losses, such as unscheduled downtime, safety issues, cost incurred [4]. The costs involved in changing the machinery parts are quite high and require a large amount of capital, market competitiveness, and the need for higher production restricts a producer from investing in such a case. As a result, to maintain the machine's effectiveness, such predictive maintenance requirements are necessary [5]. In such situations, this framework for industrial motors is crucial for developing a proactive environment. This promotes an analytical approach supported with real-time sensor data, increasing the fidelity of such prognostics driven framework increasing motor viability and efficiency [6]. Regular maintenance checks used in industries are not efficient and cannot completely prevent the losses due to unexpected contingencies during the operation of an asset. The foundation of this study is this very issue with a reactive approach for maintenance. This issue has been addressed with a case study at XYZ Industry Jaipur, where the target asset was an IE3-M induction motor used for supplying coolant at the assembly line. Our target asset i.e. induction motors show a constant degradation with time reflecting it in form of variations in electrical, mechanical and thermal signatures and also showing sporadic accidental changes. Detecting these signals and developing a system for earlier prediction requires a hybrid approach of anomaly detection and fault prediction with today's modern technologies.

The data driven diagnostic framework consists of a two-phase approach, the first phase deals with fault detection using classical machine learning algorithms trained over sensor data with thresholds from Indian and international standard codes. In second phase those thresholds are used to develop a modified version of data for long short term memory algorithm to derive temporal patterns for time series forecasting of fault and returns a continuous temporal value. This maintenance segment will now have a scope of being revolutionized by emerging artificial intelligence technology. Bearing industries such as XYZ Industry Jaipur, were experimenting and deploying fault detection, health analysis, degradation patterns, and remaining useful life estimation as a decision support system for their predictive maintenance planning of auxiliary system components such as industrial motors. Such implementation is a paradigm that is suitable for Industry 4.0 environments, where sensors are used to generate continuous operational data streams with the help of structured transformatory analytical logic for the conversion of data into actionable insights.

The objective of this study is to construct a predictive maintenance framework for a coolant supply motor during its useful life. To accurately detect early defects and predict remaining useful life to prevent unscheduled downtime and condition-based maintenance.

The rest of the paper's order is as follows. Section 2 discuss the literature review of existing fault diagnosis techniques for induction motors. Section 3 present the detailed methodology steps to be followed to carryout research study. Section 4 describe the case study on the implementation of machine learning for SCIM predictive maintenance in XYZ bearing company. At last, Section 5 concludes the paper and outlines directions for future work.

2. Literature Review

Industry 4.0 techniques helped industries nowadays to detect and predict the defects associated with risk well in time. Artificial intelligence and machine learning models play in important role in predictive maintenance. Recent studies highlighted that, machine learning and artificial intelligence are now needed for defect detection and predictive maintenance in contemporary industrial systems. Li [7] highlighted that machine learning models aid early fault identification and anomaly detection by learning trends from sensor data. Manufacturing firms adopt Industry 4.0 cutting edge technologies and Total Productive Maintenance practices as a digital maintenance [8]. Folz & Gomes [9] compared the several supervised learning models for strong performance parameters and concluded that supervised learning can reduce reliance on manual inspections and expert judgment and reducing unexpected downtimes in industrial environments.

Numerous studies have emphasized the necessity of talking about the framework for integrating industry 4.0 with predictive maintenance so that industries can benefit from using step-by-step procedures to further increase operational efficiency. Maciejewski [10] proposed a cognitive-based framework to detect and diagnose broken rotor bars under transient operating conditions in three-phase induction motors. Zhong [11] proposed a CNN-based anomaly detection method designed for small sample datasets and reported average classification accuracies were 99.75%, 99.60%, and 99.78%, respectively. A real-time predictive maintenance system using IoT sensor data for a manufacturing production line can significantly reduce downtime costs, which often include lost production, repair expenses, and quality losses after restarts [12]. Lachekhab [13] proposed an LSTM-autoencoder model to detect abnormal motor behavior using vibration data from three directions. Vlachou [14] presented an IoT-enabled predictive maintenance framework for induction motor bearings using vibration analysis with 95% classification accuracy and concluded that bearing faults account for 41–42% of induction motor failures. Akyaz & Engın [15] developed a machine-learning-based predictive maintenance system for yarn production machines using IoT data with 96% accuracy and concluded that it reduces unplanned downtime and maintenance costs compared to reactive maintenance. Shukla [16] presented a real-time anomaly detection framework for unit-phase induction motors using low-cost IoT sensors and machine learning with vibration, current, temperature, and voltage sensors data resultant good accuracy for fault prediction. Yousuf [17] presented an IoT-based monitoring and fault detection system using temperature, vibration, current, voltage, speed sensors, and GSM alerts. The system was tested on real motors and achieved 99% fault detection accuracy.

Due to the extensive use of induction motors in industrial settings and the significant costs of unplanned breakdowns, fault detection and predictive maintenance of electric motors have drawn increasing interest. Glowacz [18] identified fault diagnosis using thermal images of electric motors instead of traditional electrical or vibration signals. Hanifi [19] investigated the early fault detection for industrial electric motors using vibration and temperature sensor data. The optimized machine learning models showed strong performance in predicting faults. Pohakar [20] addressed the challenge of diagnosing simultaneous faults in three-phase induction motors, such as stator, rotor, voltage imbalance, and load variations. Gonzalez-Jimenez [21] studied common wiring and power-connection faults in induction motors using machine learning models and showed that ML models can clearly distinguish healthy motors from faulty wiring conditions with high reliability. Zhukovskiy [22] developed low-cost fault detection system for early bearing fault detection using only stator current signals making it practical for long-term industrial monitoring. Louzada [23] introduced a non-invasive stator fault detection method based on machine learning model using stray magnetic flux measured by an external coil resultant a more reliable system. Khalique [24] proposed a novel fault detection method for rotor eccentricity using only current signals. The method is non-invasive and suitable for harsh industrial environments. Ribeiro Junior [25] used Short-Time Fourier Transform (STFT) images of vibration signals as input to a convolutional neural network. The model successfully classified faults using only time-frequency representations, showing strong robustness across conditions. Ferraz Júnior [26] evaluated machine-learning models for detecting anomalies such as misalignment, overload, imbalance, and uncoupling in motor-driven systems and identified a reliable anomaly detection system.

3. Research Methodology

This section discusses the various steps to be followed to develop a predictive model and highlights the assumptions considered. For executing this unified framework, the structured approach can be understood in three mutually reinforcing strata: - Knowledge Layer - implementing the domain expertise, anomaly categorization, observational assumptions, and rationale behind the thresholds. Diagnostic Layer – extraction of concerned features, defect mapping, and condition-based fault classification. Prognostic Layer – Health index formulation, using neural network-based algorithms for modelling, and remaining useful life estimation.

3.1 System description

The generic use of motors in industries is versatile, like pumps and compressors, conveyor systems, fans and blowers and etc. In coolant supply applications, the centrifugal pumps run over 3-phase squirrel cage motors (SCIM). In this section, the motor is modeled as a multivariable system that is dynamic in nature, defined by non-linear coupling between its electrical and mechanical subsystems. For ensuring the feasibility of the proposed framework, the framework is designed for a sensor-based system, where the monitoring variables are strictly constrained. These variables are Stator phase current (I_a, I_b, I_c), Vibration (Vib_x, Vib_y, Vib_z) and Temperature (T_c). The data was acquired from respective sensors at XYZ industries ltd.

Raw sensor data, denoted as $X_{raw}(t)$, has a portion of noise and is not up to the mark for health assessment. The dimensionality characterization converts this raw time-series data into a structured, informative dimension $F(t)$ that measures motor characteristics.

4. A case study: Implementation of machine learning for SCIM predictive maintenance

This case study is based on developing a framework of predictive maintenance (PdM) of the coolant supply motor at XYZ Industry Jaipur, the methodological workflow illustrates a closed loop cycle of comprising data collection using installed sensors at the facility and gathering necessary threshold data for relevant parameters (vibrations, motor current, ambient temperature and etc.), data preprocessing, necessary synthetic data inclusion, algorithm selection, model training, and reflecting results. The purpose is to bring a transition from reactive to proactive maintenance and estimate the remaining useful life. The proposed framework is highlighted in Figure 1.

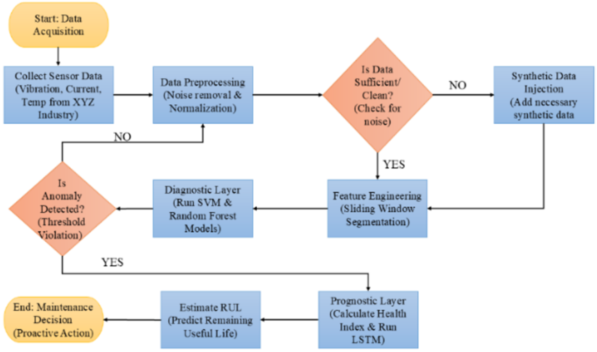

Fig. 1. Proposed framework for prediction of faults in induction motor

4.1 Data collection using sensors and standard codes

On the coolant supply motor line, sensors were installed to capture real-time data, but the data was not completely unbiased or ideal for research; hence, this study incorporated the use of some corrections to the data where needed. The real time data statistics are shown in Table 1. For anomaly detection and remaining useful life prediction, threshold limits of the respective parameters were necessary, for which ISO 20816, IEC 60034, and IEC 60038 were used.

Table 1. Real time sensor data

Parameter	Count	Mean	Standard Deviation
Current_B_Phase	40,686	20.7410	8.2823
Current_R_Phase	40,686	23.1812	4.6258
Current_Y_Phase	40,686	22.6961	4.3367
Vibration_X	40,686	0.6567	0.0000
Vibration_X_Back	40,686	0.4907	0.0000
Vibration_Y	40,686	0.5933	0.0000
Vibration_Y_Back	40,686	0.4565	0.0000
Vibration_Z	40,686	0.3682	0.0000
Vibration_Z_Back	40,686	0.4419	0.0000

The defect detection phase employs a dual modal approach using a support vector machine (SVM) for boundary-based classification and a random forest (RF) for ensemble-based fault detection.

4.2 Health Index formulation

An integrated health metric is extracted from the residual stream of sensor data. The health index serves as a continuous trend line ranging from 1.0 (nominal state) to 0.0 (critical threshold). Health index at time t which is computed as a weighted average of deviations from established ISO baselines:

$$HI(t)=1-\frac{1}{N}\sum_{i=1}^{N}\min\left(\frac{x_i(t)}{Threshold_i},1\right) \tag{1}$$

Continuous variable HI sets the limit in three zones ($HI > 0.8$ as normal, $0.6<HI\leq 0.8$ as warning, $HI \leq 0.6$ as critical). For predicting the pattern of temporal evolution of HI, algorithms such as Long Short-Term Memory (LSTM) algorithm are best suited for long-term dependencies in time series data through gated mechanisms. The cell gate state is represented as c_t and hidden state h_t are updated as follows:

$$f_t=\sigma(W_f.[h_{t-1},x_t]+b_f) \tag{2}$$

$$i_t=\sigma(W_i.[h_{t-1},x_t]+b_i) \tag{3}$$

$$c_t'=\tanh(W_c.[h_{t-1},x_t]+b_c) \tag{4}$$

$$c_t=f_t.c_{t-1}+i_i.c'_t \tag{5}$$

$$o_t=\sigma(W_o.[h_{t-1},x_t]+b_o) \tag{6}$$

$$h_t=o_t.\tanh(c_t) \tag{7}$$

The model is trained to minimize the Mean Squared Error (MSE) between the predicted health index and the real-time degradation path.

4.3 Results and Discussion

For fault detection by random forest and support vector machine, both algorithms have shown promising results as shown in Table 2. Random forest achieved an overall accuracy of 93.75% slightly outperformed by support vector machine with 94.52% overall accuracy.

Table 2. Model evaluation metrics

Diagnostic Tier	Metric Category	`Random Forest (RF)	SVM (RBF Kernel)

	Overall Accuracy	94.17%	92.83%
Global Health	Inference Speed	High (Tree Traversal)	Moderate (Support Vectors)
	Model Stability	High ($\sigma = 0.02 (approx)$	Medium ($\sigma = 0.04 (approx)$
Normal State	Precision	0.95	0.94
(Baseline)	Recall	0.98	0.97
Action State	Precision	0.89	0.86
(Warning)	Recall	0.87	0.85
Critical State	Precision	0.98	0.96
(Emergency)	Safety Recall	0.99	0.97

The Figure 2 Shows the predictive maintenance core LSTM framework with a coefficient of determination ($R^2\ score$) of 0.8904, indicating the model's capacity to explain 89% of the variance in degradation. Precise tracking and non-linearity in degradation with Root Mean Squared Error (RMSE) 37.69 cycles and Mean Absolute Error (MAE) 31.43 cycles, such results on real-life data show confidence in the viability of the model, for it can afford significant lead time to schedule maintenance actions before Health Index breaches the critical threshold due to low prediction error.

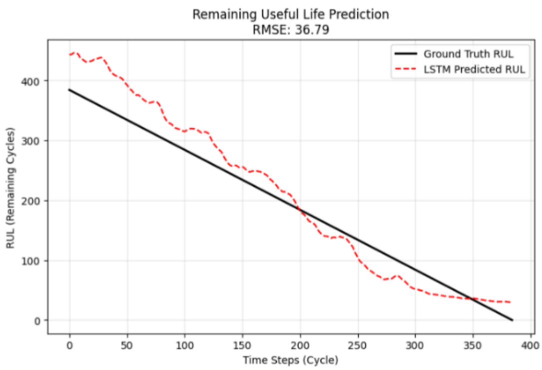

Fig. 2. Prediction of useful life prediction

5. Conclusion

This study provides a comprehensive framework for the significant gap of operational challenges for the real-world implementation of a prognostic framework. The study uses machine learning as a primary tool to bridge this gap. The two-stage methodology provides a holistic solution for anomaly detection and remaining useful life estimation. The contribution of sensor data from XYZ Industry Jaipur is extremely valuable input for successful implementation of this framework. The two-stage framework utilized SVM to detect faults and RF to isolate fault classes, followed by the application of LSTM for predicting long-term dependencies in the health index. This approach helps the system transition from reactive to proactive. Despite current progress, there is a significant future scope in fault monitoring and giving higher fidelity results for more planned maintenance of assets; the use of generative adversarial networks (GANs) is still under scope on this issue.

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