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An IOT-based Multi-Sensor Digital Twin for Predictive Maintenance of Industrial Motors

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***Abstract*— More factories need maintenance that's reliable and cheap. That need pushes factories to use Digital Twin technology with Artificial Intelligence (AI). We present a multi-sensor AI-driven Digital Twin design for maintenance of a 37 kW (50 HP) industrial induction motor. The Digital Twin design uses vibration sensors, temperature sensors and current sensors to record the induction motor's wear, thermal wear and electrical wear. I set up the Masibus scanner to read sensor data in real time. The Masibus 85XX+ universal scanner then sends the data using Modbus RTU over an RS-485 link. I built a Digital Twin application in a Python environment. The Digital Twin application shows the operating parameters as they happen. The Digital Twin application also runs calculations. I apply feature engineering techniques to the sensor data. Feature engineering techniques add features and rate-of-change indicators. Feature engineering techniques turn the data into inputs for a Random Forest regression model. The Random Forest regression model predicts the Remaining Life (RUL). The Random Forest regression model gives a Remaining Life (RUL) prediction that I can use to plan maintenance. I tested the system performance against ISO 10816 Class II vibration standards. I found that the proposed model gives a prediction accuracy with an R Squared (R2) of 0.91 and a Mean Absolute Error (MAE) of 2.45 hours. I see that the multi-sensor approach makes the system performance stable and reliable compared to single-parameter monitoring techniques. I also integrated the system performance with the ThingSpeak IoT platform. The integration lets the ThingSpeak IoT platform provide monitoring and historical data logging. The integration makes the framework able to grow and fit Industry 4.0 applications.**

***Index Terms*— Digital Twin, Predictive Maintenance, Induction Motor, Multi-Sensor Data Fusion, Random Forest, ISO 10816, Modbus RTU.**

I. INTRODUCTION

Industrial induction motors are used in the manufacturing sector in the power plants, the pumping systems and the process industries as these motors have durability and efficiency. Because of a failure of an induction motor, there is unplanned downtime and production loss, as well as higher maintenance costs and safety issues [2]. Therefore, we have to keep the industrial induction motors running in good condition. Finding faults in the industrial induction motors as early as possible is a must in the industrial environment [5]. Traditional maintenance methods do not work well for the systems [3]. It is seen that reactive maintenance can cause failures.

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It is also seen that due to the usage of preventive maintenance, there may be part replacements and higher operating costs. The condition-based maintenance techniques that use vibration or temperature monitoring have improved fault detection.

Most current systems rely on sensor analysis and fixed threshold alarms [6]. I have noticed that the methods do not capture the wear patterns of motors. The industrial motors run under varying loads and environmental conditions.

The methods miss those patterns [14]. I notice that the rise of Industry 4.0 technologies makes Digital Twin a practical solution for monitoring and decision making [1]. Digital Twin provides a time copy of a physical asset. Digital Twin stays updated with live sensor data [8]. When Digital Twin works with intelligence and machine learning, Digital Twin enables maintenance.

Digital Twin estimates the Remaining Useful Life (RUL) of equipment by just finding faults [7] [18]. Recent research shows the value of multi-sensor data fusion.

Multi-sensor data fusion helps get health assessments of rotating machinery. I have seen that multi-sensor data fusion brings together vibration data, temperature data and electrical current data. Vibration data, temperature data and electrical current data each give a view of wear, thermal wear and electrical wear. The three data types together give a picture of the rotating machinery condition. Machine learning algorithms turn the data into health assessments. Machine learning algorithms, combined with models such as Random Forest, work well with complex factory data. Random Forest models can handle the noise and the irregular patterns that appear in the data.

The studies in [9] [19] and the work in [4] [12] support these points. The research paper presents an AI-based sensor twin system for predictive maintenance of a 37-kW industrial induction motor. The digital twin system predicts problems before they occur in industrial motors. Following the given list of the contributions of the study:

- The real-time Digital Twin system has been designed to integrate the vibration sensor, the temperature sensor and the current sensor. In the real-time Digital Twin system, communication with the sensors takes place via Modbus RTU.
- For the prediction of RUL (Remaining useful life) by using random forest regression, a multi-feature machine learning model is developed.
- Feature engineering technique is used to know the degradation trends and interconnections of sensors.
- A desktop-based dashboard system is created for monitoring, and a cloud system is connected to it.

II. Related Work

There are many researches are going on on condition monitoring and predictive maintenance currently in the industries for industrial motors. Conventional works have only focused on fault diagnosis through vibrations, hence these are mostly responsive only to the bearing fault and mechanical misalignment [5]. There are different ways, such as Fast Fourier Transform (FFT), envelope analysis, and statistical feature extraction, which are used entirely in rotating machinery [6]. Only vibration-based techniques never guarantee that fault prediction can be done accurately while the load is changing. Their performance is not good because of noisy industrial surroundings, which gives false alarms [14].

To predict and monitor the faulty condition and diagnose the fault of motors, many researchers are currently trying to use machine learning models [2]. Artificial Neural Networks and Support Vector Machines are used to detect motor health conditions based on vibration data [15].

The current researches are focusing on multi-sensor data fusion for improving the excellence of condition monitoring systems [9].

It is seen that by combining vibration, temperature, and electrical current signals, fault detection can be more accurate and less chances of sensor noise [19].

Digital Twin architectures have been suggested by many papers for rotating machines, which integrate sensor data with simulation or analytics models [7].

Random forest-based models are successfully being employed in industrial prognostics [4], [16]. These types of models can work very well even in noisy conditions and with nonlinearity of the data [12].

Based on the literature review, a research gap has been identified in the development of a real-time, multi-sensor Digital Twin system that works with machine learning-based RUL prediction. This present work finds real issues and solved it by introducing an AI-based Digital Twin system for industrial induction motors that uses real-time hardware-in-the-loop data acquisition.

III. Problem Statement and Motivation

Currently, in industries, the maintenance departments mainly focus on time-based inspections, or they use fixed threshold alarms, by which the remaining motor life is not estimated. And in many cases, condition monitoring systems use just one sensing parameter, generally vibration, to find out the health of a motor. But single sensor systems may produce false alarms, as well as it can also miss early-stage faults due to the combined action of mechanical, thermal, and electrical degradation mechanisms. Although machine learning techniques are being utilised rapidly in fault diagnosis, many current solutions in this area are still more oriented towards fault classification rather than prognostics. Due to a lack of run-to-failure datasets and sensor noise, it is difficult to predict the Remaining Useful Life (RUL) of industrial motors. Many methods that are described in the literature survey do not have real-time usage and are not integrated with industrial communication standards.
So, I introduced a solution that can run in factories and gives a view of motor health and RUL estimation.

IV. Methodology and System Architecture

The Digital Twin framework has a Physical Layer that holds sensors and a motor. The Digital Twin framework has a Communication Layer that handles data acquisition. The Digital Twin framework has an Application Layer that runs the Digital Twin and AI. The system architecture is shown in Figure 1.

A. Experimental Setup and Physical Layer

The experimental setup centres on a 37-kilowatt (50-horsepower) three-phase industrial induction motor, with complete hardware and software specifications outlined in Table I. The experimental setup uses three industrial-grade sensors. The experimental setup captures the multi-physics degradation behaviour:

- Vibration Sensor: The piezoelectric vibration transmitter is mounted on the motor bearing housing. The piezoelectric vibration transmitter captures vibrations in millimetres per second.
- Temperature Sensor: We install the RTD (Pt-100) Temperature Sensor on the stator winding slot to monitor stress in degrees Celsius.
- Current Sensor: The Current Transformer is connected in series to the motor phase line and measures the load in Amps.

B. Data Acquisition and Communication Layer

The analog signals (4-20mA / 0-10V) from the sensors are given a Masibus 85XX+ Universal Scanner. The scanner digitises the raw sensor signals and acts as a Modbus Slave. Data transmission is achieved using the Modbus RTU protocol over an RS-485 serial communication link. A USB-to-RS485 converter interfaces the DAQ unit with the host computer, ensuring reliable data transfer with high noise immunity suitable for industrial environments.

C. Digital Twin Application Layer

Digital Twin software is developed using python language. The Tkinter framework creates the graphical user interface for the Digital Twin. The software architecture of the Digital Twin contains the following modules:

- Modbus Client: The Modbus Client uses the pymodbus library. The Modbus Client polls sensor data from the Masibus scanner’s holding registers (Address 30001 30003), at a sampling rate of one hertz.
- Data Buffer & Feature Engineering: The rolling window buffer stores the ten samples. The rolling window buffer calculates features, like the mean and the standard deviation. The rolling window buffer calculates trend indicators like the rate of change. The statistical features and the trend indicators are inputs for the AI model.
- AI Inference Engine: The pre-trained Random Forest Regressor model is embedded within the application to predict Remaining Useful Life (RUL) in real-time.
- Cloud Integration: The system uploads processed data to the ThingSpeak IoT cloud platform every 5 minutes for remote monitoring and historical analysis, as shown in Figure 4.

TABLE I: SYSTEM SPECIFICATIONS

Component	Specification
Test Motor	3-Phase Induction Motor, 37 kW, 415V
Controller	Masibus 85XX+ Universal Scanner
Communication	Modbus RTU over RS-485
Software	Python 3.x (Tkinter, Scikit-learn, PyModbus)
AI Model	Random Forest Regressor

V. MACHINE LEARNING MODEL AND FEATURE ENGINEERING

While working on industrial induction motors It is found that effective modelling of non linear degradation behaviour is needed for a Remaining Useful Life (RUL) prediction. It's also seen that unprocessed sensor data does not give information to show the degradation trend over time. The data alone is not enough. In the present study, the work uses feature engineering methods. We pair feature engineering methods with a regression model that uses machine learning. The regression model and machine learning together aim for prognostics.

A. Dataset Preparation

Because safety, cost and operation limits make it very hard to collect run-to-failure data for high-power industrial induction motors, we cannot get that data in factories. To solve this problem a synthetic degradation dataset is created. We use the degradation dataset to train and test the Remaining Life (RUL) prediction model. The dataset is made to copy the real wear patterns we see in industrial induction motors. The synthetic dataset shows how the motors wear down over time.
Three condition indicators are defined:

- Vibration Signal: The Vibration Signal increases gradually over time. The Vibration Signal shows bearing wear and mechanical imbalance. The Vibration Signal adds Gaussian noise to simulate sensor noise.
- Temperature Signal: With increasing load and insulation ageing of windings, signals are produced and reflect thermal stress storage in stator windings.
- Current Signal: signals vary as per electrical load conditions, and many electrical conditions are responsible for this.

B. Feature Engineering

The ability of the machine learning model to predict the remaining useful life of the motor is improved by extracting time features from the raw sensor data, which are used in this paper (as shown in Figure 2).

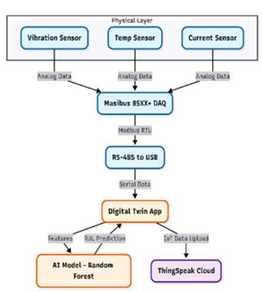
- Rolling Mean represents the average sensor behaviour over a recent period of time.
- Rolling Standard Deviation is used for the evaluation of variability and signal dispersion.
- Rate of Change measures how speedily degradation between successive measurements takes place.

C. Machine Learning Model Selection

There are many reasons to use this machine learning technique, but one of the reasons why we used the Random Forest regressor for predicting RUL is its industrial applicability. Different decision trees are used in Random Forest models, so they are able to handle nonlinear relationships, noisy data, and feature interactions effectively. Besides that, Random Forest is more computationally efficient and interpretable than deep learning, thus it is a good option for real-time deployment in a Digital Twin framework. The model was trained on a set of engineered features and verified through various standard regression metrics. Feature scaling was done to have a uniform input representation, and model hyperparameters were tuned to achieve a good trade-off between prediction accuracy and computational efficiency.

Real-Time Model Deployment

A Random Forest model that has been trained was used inside the Digital Twin environment to make real-time RUL predictions. Live sensor data can be processed continuously in the same way as features were computed during the training of the ML model, thus maintaining the consistency of features between offline training and online inference. The predicted RUL values keep updating in real-time and are thus displayed on the Digital Twin dashboard, which allows proactive maintenance decision-making.
Detection Risk: Low-Moderate



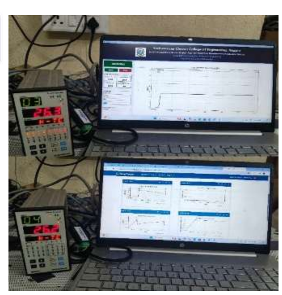


Figure 1. Block Diagram Figure 2. Complete system view

VI. Experimental Setup and Results

A. Experimental Setup

The Digital Twin system is set up on a bench that mimics a 37 kW (50 HP) industrial induction motor. Three industrial grade sensors are attached those are piezoelectric vibration transmitter, RTD (Pt 100) temperature sensor and Current Transformer (CT) interfaced to a Masibus 85XX+ Universal Scanner. The Masibus 85XX+ Universal Scanner works as a Data Acquisition (DAQ) unit. The Masibus 85XX+ Universal Scanner sends data via Modbus RTU, over RS 485 to the host computer every second.

B. Threshold-Based Monitoring Results

The Digital Twin dashboard showed real time sensor data (as shown in Figure 3). We validated the condition monitoring logic by testing the system against ISO 10816 standards, for Class II machinery. The health status was divided into categories as follows:

- Healthy: Vibration < 2.8 mm/s.
- Warning: Vibration 2.8 – 4.5 mm/s.
- Critical: Vibration > 4.5 mm/s.

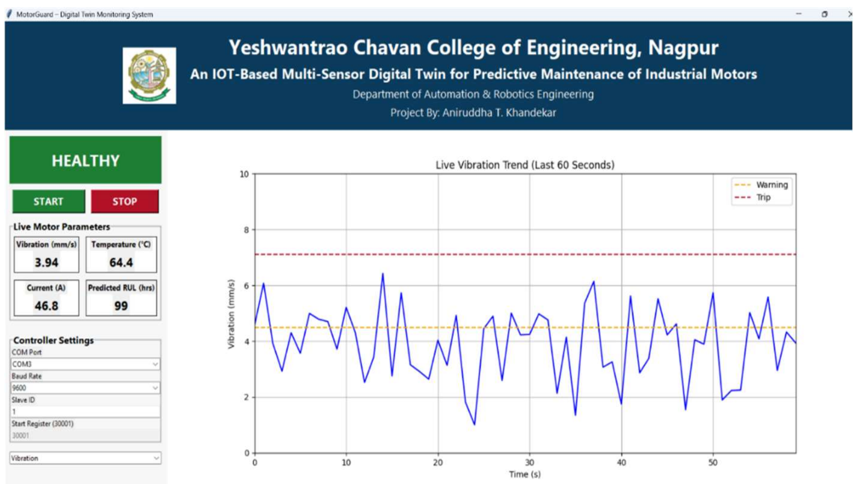


Figure 3. Python Dashboard

In experiments It's seen that the multi-sensor approach cut alarms compared with single sensor monitoring. The multi-sensor approach proved better. The temperature and current data gave context to the mechanical vibration spikes.

C. RUL Prediction Performance: The Random Forest-based RUL

The prediction model gave outputs while the prediction model ran in time. The prediction model did not use alarms. The predicted RUL values showed a drop that matched the mean and rate of change logic. The system updated RUL predictions on the Python dashboard as new data arrived. The trained model worked with data inputs. The trained model gave time to plan maintenance. The overall performance metrics for the prediction model are summarised in Table II.

TABLE II: PERFORMANCE METRICS

Performance Metric	Value	Description
R-Squared (R2)	0.91	Indicates 91% variance explained by the model
Mean Absolute Error (MAE)	2.45 hours	Average deviation in RUL prediction
Root Mean Squared Error (RMSE)	3.12 hours	Standard deviation of prediction errors
Prediction Horizon	120 hours	Maximum look-ahead time for prognostics

D. Cloud-Based Monitoring Results the ThingSpeak IoT integration

The transmission of the sensor data is enabled and the RUL predictions, at five minute intervals. The sensor data is uploaded on cloud. Uploaded the RUL predictions for access, via a web API. The web API shows asset management. The web API shows trend analysis.

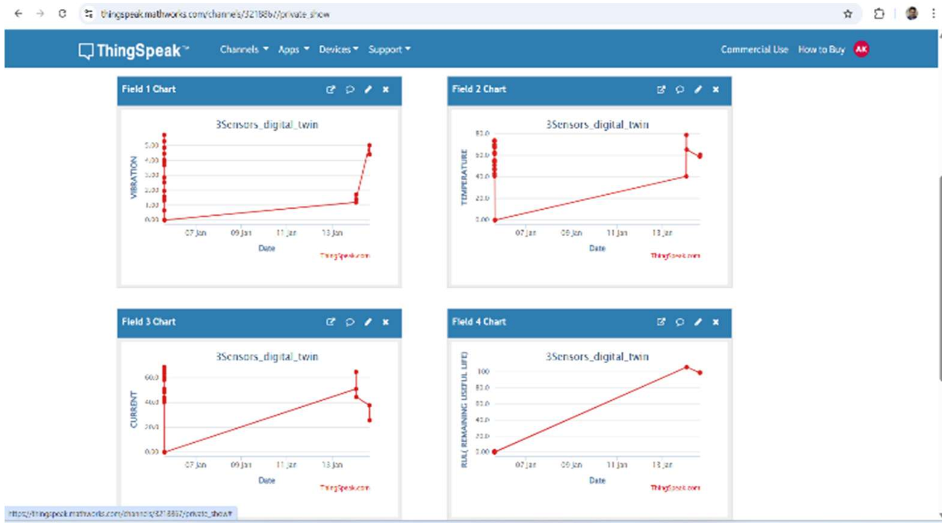


Figure 4. Thingspeak cloud

E. Discussion

The experimental results show that the proposed Digital Twin framework is capable of combining real-time sensing, AI-based prognostics, and cloud connectivity into one monitoring system.

Whereas traditional condition monitoring systems are single-parameter, parameter threshold-based, the proposed method makes use of multi-sensor data fusion and machine learning to offer a health assessment that is not only more reliable but also more informative. The Random Forest model demonstrated strong performance because it is flexible in dealing with situations where the relationships are nonlinear, and the industrial data is noisy.

Such systems are best suited to medium and large industrial motors where downtime without prior notice results in a very high cost. The modular software design also facilitates adding more sensors or more advanced predictive models in the future.

VII. Conclusion and Future Scope

A. Conclusion

This research paper presented the realisation of a machine learning Digital Twin model that allows real-time monitoring and Remaining Useful Life (RUL) prediction of an industrial induction motor. This system successfully combined multi-sensor data by using the Modbus RTU communication protocol, and it also combined machine learning and cloud-based monitoring into a single platform.

As we saw from experimental results, the digital twin mirrors the condition of a 50 hp motor accurately. From the data of vibration, temperature, and current, the motors' thermal, electrical and mechanical conditions were evaluated. The random forest regression, which is used in this paper, can work efficiently with nonlinear data.

B. Future Scope

There are even more possibilities for expanding the system's capabilities in future research, as the developed one performs very well.

One suggestion to improve the Digital Twin framework is to add more sensing modalities to the fault diagnosis component, e. g., acoustic emission or oil debris analysis, which in turn would lead to higher diagnosis accuracy.

Advanced deep learning architectures, such as Long Short-Term Memory (LSTM) networks, can be used to model the long-range dependencies in the data, which, as a result, leads to a significant improvement of RUL prediction accuracy.

Moreover, the implementation of the system on edge computing devices can be considered in the future to provide a low-latency service that is also highly scalable in large industrial environments.

Furthermore, testing the proposed method on long, term run, to, failure datasets obtained from different

Motors working under different load conditions would facilitate the demonstration of the method's robustness and applicability to other scenarios.

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