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MACHINE LEARNING BASED PREDICTIVE MAINTENANCE OF MOTOR USING SINGLE MODEL ANALYSIS

Rohit Sonawane[#1], Advait Acharya[#2], Shivam Pandey[#3], Sagar Chougule [#4]

Ms. Garima Gurjar (Assistant Professor, Academics)

Electrical Engineering, Atharva College of Engineering, Malad (W), Mumbai.

ABSTRACT -

Condition monitoring together with predictive maintenance of electric motors and other equipment used by the industry avoids severe economic losses resulting from unexpected motor failures and greatly improves the system reliability. This paper describes a Machine Learning architecture for Predictive Maintenance, based on Machine Learning approach. The system was tested on a real industry example, by developing the data collection and data system analysis, applying the Machine Learning approach and comparing it to the simulation tool analysis. Data has been collected by various sensors. With the help of this paper, we want to monitor and increase the life span of Electric motor and other equipment's.

I. INTRODUCTION

Recently, with the emergence of Industry 4.0 (I4.0), smart systems, machine learning (ML) within artificial intelligence (AI), predictive maintenance approaches have been extensively applied in industries for handling the health status of industrial equipment. Due to digital transformation towards I4.0, information techniques, computerized control, and communication networks, it is possible to collect massive amounts of operational and processes conditions data generated form several pieces of equipment and harvest data for making an automated fault detection and diagnosis with the aim to minimize downtime and increase utilization rate of the components and increase their remaining useful lives. Predictive maintenance is inevitable for sustainable smart manufacturing in I4.0. Machine learning (ML) techniques have emerged as a promising tool in Predictive maintenance applications for smart manufacturing in I4.0, thus it has increased attraction of authors during recent years. This project aims to provide a comprehensive review of the recent advancements of ML techniques widely applied to Predictive maintenance for smart manufacturing in I4.0 by classifying the research according to the ML algorithms, ML category, machinery, and equipment used, device used in data acquisition, classification of data, size and type etc. This project proposes predictive maintenance of electric motor based on sensors that monitor various reasons for failures such as Transient voltage ("surges" or "spikes"), Voltage imbalance, Current imbalance, Vibration, High operating temperature, Motor overload, Misalignment, Moisture etc. Machine learning prediction models will be used for predictive maintenance of motor and to predict failures in motor.'

These are the reasons why we are building this project:

• Breakdown maintenance was practiced in the early days of production technology and was reactive in nature. Equipment was allowed to run until a functional failure occurred. Secondary damage was often observed along with a primary failure. This led to time-based maintenance, also called preventive maintenance

• Due to the high maintenance costs when using preventive maintenance, an approach to rather schedule the maintenance or overhaul of equipment based on the condition of the equipment was needed. This led to the evolution of predictive maintenance and its underlying techniques.

• Predictive maintenance requires continuous monitoring of equipment to detect and diagnose defects. Only when a defect is detected, the maintenance work is planned and executed.

• Today, predictive maintenance has reached a sophisticated level in industry. Till the early 1980s, justification spreadsheets were used in order to obtain approvals for condition-based maintenance programs. Luckily, this is no longer the case.

• The advantages of predictive maintenance are accepted in industry today, because the tangible benefits in terms of early warnings about mechanical and structural problems in machinery are clear. The method is now seen as an essential detection and diagnosis too that has a certain impact in reducing maintenance costs, operational vs. repair downtime and inventory hold-up.

The main elements of distribution system assessment are:

1. Increase in machine productivity

2. Improved repair time & product quality

3. Increase machine life

4. Resources for repair can be properly planned.

SOFTWARE USED

- Arduino IDE – For coding ESP32 Microcontroller
- Fritzing – For Circuit Designing
- ThingSpeak – For Cloud Storage
- Spyder – For ML Code

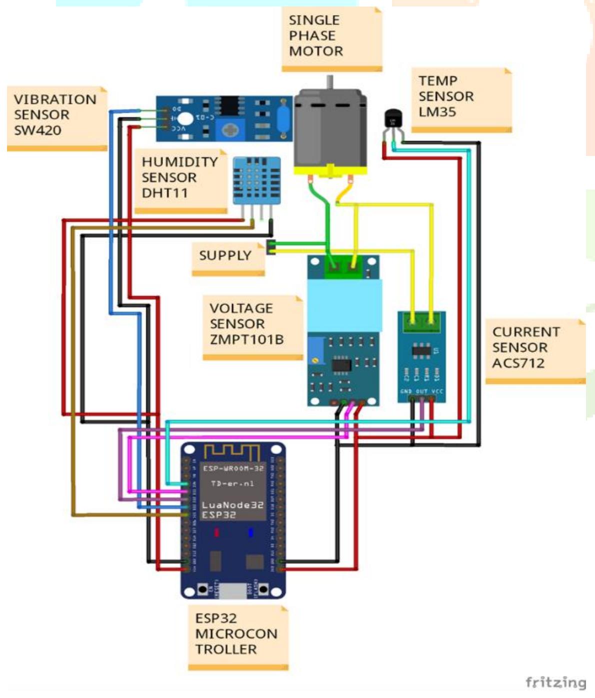


Fig. 1

II. LITERATURE REVIEW

1. Based on the paper Condition Based Techniques and Predictive Maintenance for Motor by Aniket A. Manjare & Babasaheb G. Patil in 2021, the most commonly used ML technique for PdM is the RF algorithm, as it has been applied to numerous motors, motor fitted systems, including rotating equipment, industrial motors, cutting machines, wind turbines, vending machines, and many others.

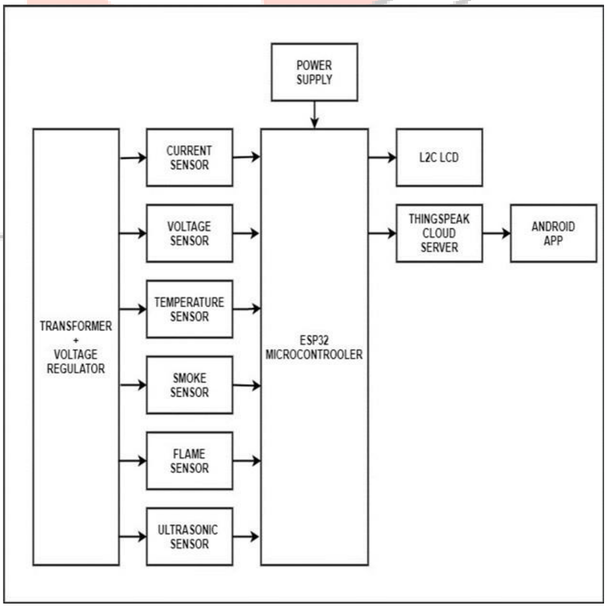
2. Based on the paper on Advanced Predictive Maintenance with Machine Learning Failure Estimation in Industrial Packaging Robots by O. KOCA, O. T. Kaymakci and M. Mercimek in 2020, The MLP strategy can deal with unforeseen downtime events. It will reduce unscheduled downtime costs of output tremendously. Theoretical and realistic observation of the defects found.

3. Based on the paper on Multisensor data fusion for gearbox fault diagnosis using 2- Dconvolutional neural network and motor current signature analysis by Moslem Azamfara, Jaskaran Singha, Inaki BravoImazb, Jay Lee in 2020, the paper proposes a novel multisensor data fusion methodology based on 2-D convolutional neural network and for gearboxes FDD using MCSA. Multiple motor current sensors are used to monitor and diagnose the fault types in a gearbox under different working conditions.

4. Based on the paper on Machine Learning Predictive Maintenance on Data in the Wild by A.Binding, N. Dykeman and S. Pang in 2019, The fit of the models remained compatible with a different system of measurement. Assisted judgment thresholds work higher than LR, with RF and XGBoost. Both algorithms worked equally better in ROC terms.

5. Visualisation of the data can be done using Python Modules such as matplotlib, seaborn, ggplot etc.

III. METHODOLOGY



III. METHODOLOGY

1. Sensors will be used to monitor and collect data.

2. The data collected will be passed to NodeMCU Microcontroller.

3. NodeMCU microcontroller is chosen because it supports inbuilt Wi-Fi. Hence data can be directly stored to cloud storage over the internet.

4. Cloud Storage that will be used for storing data is ThingSpeak Cloud. It supports data storage along with

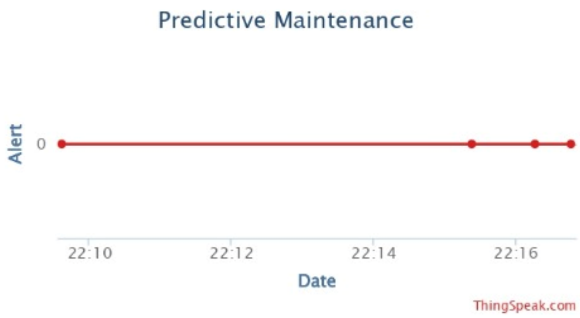
visualizations. Once sufficient amount of data is collected it can be exported into Excel .csv format.

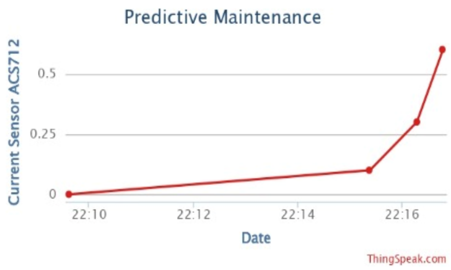
5. The data exported from ThingSpeak Cloud is the dataset which will be used as a dataset for Machine Learning.

6. Pre-processing steps such as exploration, cleaning and transformation of dataset will be done using Python.

7. Machine learning prediction models such as Random Forest, Decision Tree, Naïve Bayes etc. can be used for predictive maintenance of motor and to predict failures in motor.

IV. RESULTS





PdM (Predictive Maintenance) is a strategy viable adopted when dealing with maintenance issues given the increasing need to minimize downtime and associated costs. The methodology has been implemented in the experimental environment on the example of a real industrial group, producing accurate estimations.

These are the Graphs we will receive every 2 minutes from all the 6 sensors. Continuous monitoring of the Electrical equipment will take place with the help of this Project.

Overall Accuracy 0.95

Average Accuracy 0.92.

IV. CONCLUSION

Predictive maintenance requires continuous monitoring of equipment to detect and diagnose defects. Only when a defect is detected, the maintenance work is planned and executed. Today, predictive maintenance has reached a sophisticated level in industry. Till the early 1980s, justification spreadsheets were used in order to obtain approvals for condition-based maintenance programs. Luckily, this is no longer the case. The advantages of predictive maintenance are accepted in industry today, because the tangible benefits in terms of early warnings about mechanical and structural problems in machinery are clear. The method is now seen as an essential detection and diagnosis too that has a certain impact in reducing maintenance costs, operational vs. repair downtime and inventory hold-up

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