Developing Fault Identification And Classification of DC Motor Control Kit Using Predictive Maintenance

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Abstract- *The main objective of an industrial facility or utility is to maximize the quantity and quality of production by maintaining the lowest production and maintenance costs. This can only be achieved when the plant is operated efficiently, so proper maintenance of the plant is necessary. There are several strategies, the most significant of which is industry 4.0 predictive maintenance. Predictive maintenance helps to predict errors that will occur after processing data and warns the operator. This predictive maintenance technology helps reduce unplanned maintenance time, improves the cost factor of plant maintenance and also optimizes the life expectancy of the equipment. In this work, the design and development of the predictive maintenance algorithm is observed for predicting Healthy and Faulty data from real time data with on-board implementation on DC Motor kit.*

Keywords- Predictive Maintenance, DC motor, Fault Identification, SVM, Industry 4.0, MATLAB.

I. INTRODUCTION

Industrial maintenance has evolved since the early days of the industrial revolution, when maintenance was mostly reactive in nature. This suggests that maintenance was only performed in response to equipment breakdowns. This led to unforeseen downtime and significant maintenance costs. However, as new technologies and equipment have been developed, maintenance practises have become more sophisticated and proactive. Maintenance tasks are now carried out on a predetermined basis, utilising modern monitoring and predictive technologies. To minimise downtime and maximise production, any industrial organisation must implement an effective maintenance strategy.

Companies can use a variety of maintenance methods, including reactive, preventive, and predictive [1] as shown in fig 1.

Reactive maintenance is the least desirable type of maintenance because it entails restoring equipment after it has already failed. Preventive maintenance entails performing routine maintenance on equipment to keep it from breaking down. Predictive maintenance employs advanced monitoring technology to predict when equipment may break, allowing maintenance tasks to be planned ahead of time. Industrial organisations may ensure that their equipment is functioning at full capacity by selecting the correct type of maintenance approach, resulting in greater production and reduced downtime.

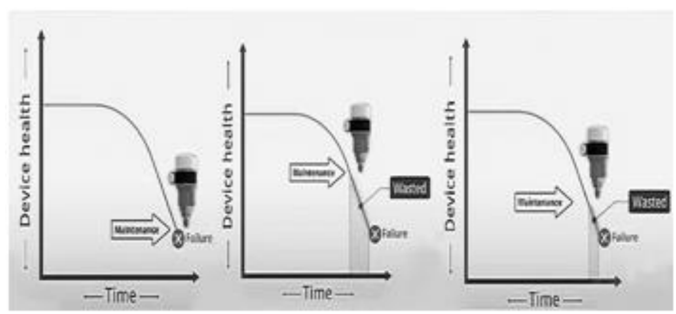


Figure 1: Types of Maintenance (Ref – RealPars)

Predictive maintenance is an important component of Industry 4.0, the fourth industrial revolution marked by the incorporation of digital technology into manufacturing and other industrial processes shown in fig 2 [2]. Industry 4.0 permits the collection and analysis of huge amounts of data from sensors and other sources in order to optimise and raise the efficiency of industrial operations. In Industry 4.0, predictive maintenance combines modern sensors and analytics tools to monitor equipment conditions and predict maintenance needs in real time. This enables proactive care and decreases the likelihood of unplanned downtime. One advantage of predictive maintenance in Industry 4.0 is that it allows manufacturers to shift from reactive to proactive maintenance procedures. Manufacturers can reduce maintenance costs, boost equipment uptime, and improve overall production by anticipating future faults.

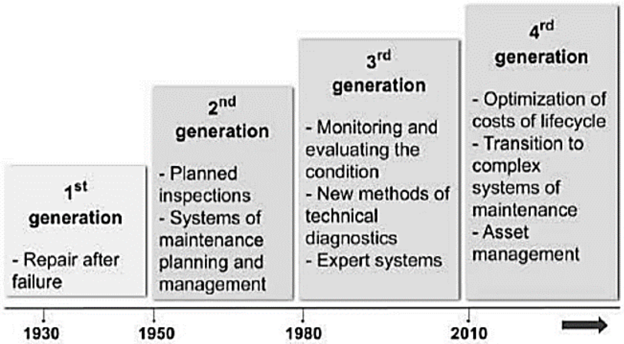


Figure 2: Evolution of Maintenance (Ref: [2])

There are several types of predictive maintenance methods, including: 1) data-driven methods; 2) model-based method; and 3) hybrid method [3]. Using machine learning and statistical methodologies, the data-driven strategy collects data from numerous sources to predict equipment breakdowns and maintenance requirements. The model-based method uses physics-based models to simulate equipment behaviour and anticipate maintenance requirements under various operating situations. The hybrid approach combines data-driven and model-based approaches to produce more precise and dependable predictions of equipment performance and maintenance needs.

Some other approaches of predictive maintenance are available in which PdM approaches include vibration analysis with the Fast Fourier transform [4], predicting power system health through the ageing mechanism [5], and finding hot spots in transformers with thermal imaging [6]. PdM can also be achieved by applying anomaly detection based on thermodynamic equations for compressor discharge temperature [7], neural network analysis of data patterns [8], and root cause analysis to discover the underlying reasons for equipment failures [9].

Predictive maintenance strategies based on PHM and CBM techniques are critical tools for industries, especially in the age of rising ICTs [10]. These rules assist businesses in properly managing maintenance and lowering expenses by spotting possible difficulties early [11]. The OSA-CBM principle is a critical industry standard that allows for the early diagnosis of maintenance issues via online data analysis [12]. Industries can avoid equipment failures by embracing this innovative technology.

Section 1: of this study includes an introduction to PDM. Section 2: PDM Architecture, the algorithm for PDM is included in Section 3. Section 4 covers PDM implementation.

II. ARCHITECTURE OF PDM.

A predictive maintenance system's architecture typically consists of multiple layers, beginning with the data acquisition layer, where sensors and other data sources collect information about the operation of the equipment. In the data preparation layer, this data is pre-processed and filtered before being fed into the machine learning layer, where algorithms are taught to discover patterns and abnormalities in the data. Finally, the maintenance execution layer is in charge of doing any necessary repairs or replacements. This design enables organizations to detect and address equipment issues before they cause costly downtime, thereby lowering maintenance costs as shown in fig 3.

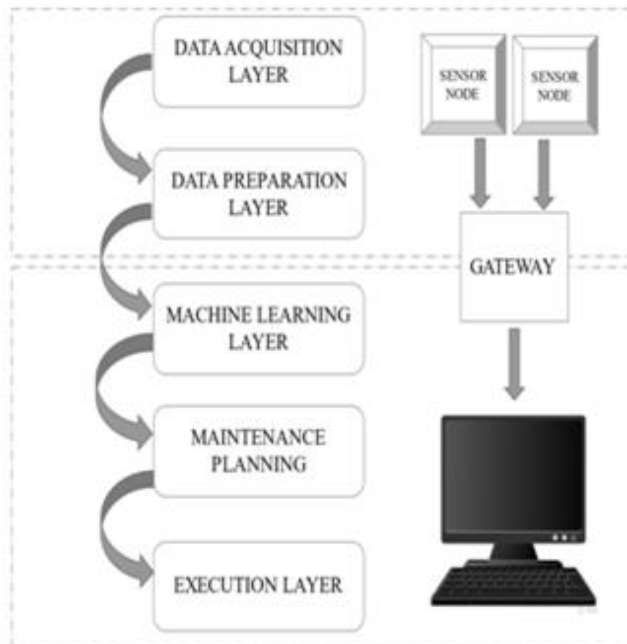


Figure 3: Architecture of Predictive Maintenance

III. PREDICTIVE MAINTENANCE ALGORITHM

An algorithm is a set of instructions that a computer uses to solve a problem or accomplish a task. It is a set of well-defined rules that are used in computer programmes for a variety of purposes, such as data analysis, machine learning, and optimization. The phrase is taken from the name of the Persian mathematician Muhammad ibn Musa al-Khwarizmi. In Predictive Maintenance Algorithm there are main six steps.

They are as follows:

Step 1: The first step is to collect data from various sources, such as sensors, machines, and systems.

Step 2: The collected data is then pre-processed to remove any irrelevant or noisy data, and to transform it into a suitable format for analysis.
Step 3: In this step, features that are relevant to the maintenance task are extracted from the pre-processed data.
Step 4: A predictive model is developed using the extracted features, which can detect anomalies and predict equipment failures.
Step 5: The developed model is validated using historical data or test data to ensure its accuracy and reliability.
Step 6: The final step involves deploying the predictive model in a real-time production environment, where it can monitor the equipment and provide maintenance alerts when necessary.

The next figure shows the workflow of Predictive Maintenance Algorithm source of the figure is taken from the official site of MATLAB.

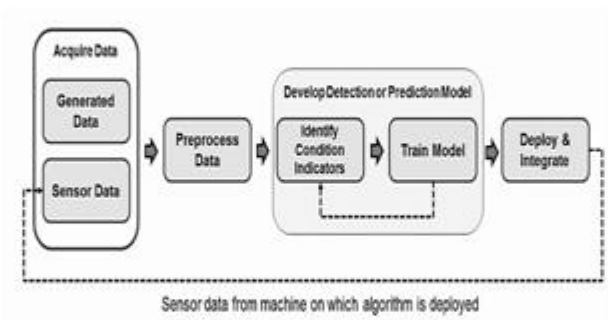


Figure 4: Workflow of PDM Algorithm (Ref: MATLAB)

IV. IMPLEMENTATION OF PDM

A. DC MOTOR CONTROL KIT

The DC Motor Control Kit is a versatile device designed to educate and show the foundations of motor control in a variety of ways. It is low-cost, very portable equipment. The uniquely developed kit gives students a hands-on plant experience right on the bench. The kit includes a DC motor with an encoder, an integrated interface, and driver electronics. An interactive front-end software allows users to create high-end control algorithms using either LabVIEW or MATLAB/Simulink programmes. The kit, developed under the MHRD Virtual Labs: Remotely Triggered Labs project through their NMEICT plan, is in line with the Make-in-India drive and the Government of India's Atmanirbhar Bharat Mission.

Figure 5: DC Motor control kit by Carimo Technologies

Table -1: DC Motor kit Technical Specification

Motor Type:	Permanent magnet DC brushed motor with manually variable load
Control:	Through PC frontend software
PC Connectivity:	USB
Software:	Free Runtime Engine Software provided
Construction Material:	ABS
Power Source:	230 V AC

The kit comes with 3 disks with magnets on it. Which are used for experimental purpose.

B. DATA COLLECTION

The DC Motor Control Kit can be effortlessly connected to the computer via the USB connector. The DC Motor Control Kit is controlled by a LabView Runtime engine. The runtime engine has PWM as an input and speed (RPM) as an output. The real-time data is saved in the excel file format and can then be used for machine learning tasks. The excel file is divided into three columns: time, input PWM, and output speed. For this work, I gathered data from DC motors with PWM values ranging from 30 to 150. Data is collected for DC motors with and without loads.

C. PROCESSING OF DATA

The DC motor data is collected using LabView Runtime. For the various values of PWM ranging from 30-150. The data is labelled for binary classification with two classes: "healthy" and "faulty." The classification of data is done with the assumption that when there is no load applied to the DC motor, the motor is working in a healthy condition, and when load is applied to the motor, the motor is in a faulty condition. For this classification, the data of the DC motor is collected with and without load for each PWM value. The Data which is collected is used for training the machine learning model.

MATLAB is the essential software used to implement the predictive maintenance fault detection and classification application. MATLAB provides a predictive maintenance toolbox that includes the Diagnostic Feature Designer tool and the Classification Learner app.

The Diagnostic Feature Designer tool is used to extract the features, and the Classification Learner app is used to train using various machine learning models. After collecting the data from the DC motor, it is processed and trained in the classification learner app. Inside classification learner app, there are three features and one category. It is trained with 5 kfold of cross validation. 30% of the data is selected for testing purpose and 70% data is trained. Further the data is trained for all available machine learning models. The model with the high accuracy and minimum time to train is selected and the trained model is then exported for the testing purpose. The machine learning model's accuracy and time is mentioned in the below table.

Table -2: Observation Table

ML Model	Accuracy	Prediction Speed	Time/secs
Tree	100%	~230000 obs/secs	8.472
Naïve Bayes	68%	~400000 obs/secs	1.6488
SVM	100%	~370000 obs/secs	4.5943
KNN	100%	~110000 obs/secs	16.127

After training the data in the classification learner app, I adopted the Support Vector Machine (SVM) machine learning model for training since it provides higher accuracy, more observations per second, and takes less time to train the model than other machine learning algorithms. Scatter Plot is obtained for SVM algorithm as shown in fig 6.

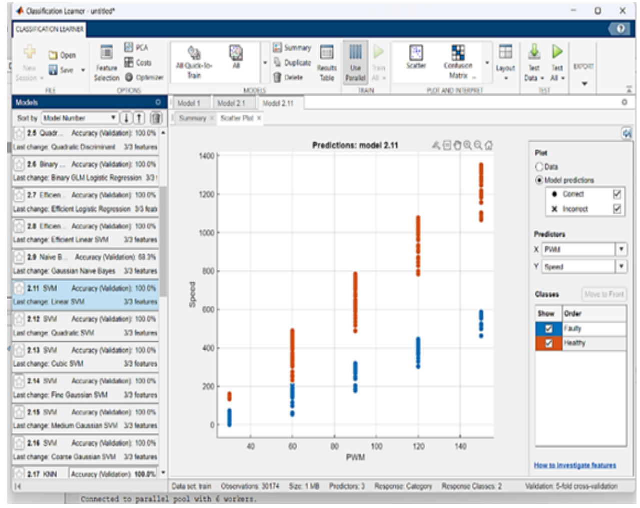


Figure 6: Scatter Plot of trained data

It is observable that the data collected from the DC motor kit is Highly Separable data, which is easily trained by the support vector machine algorithm. In the scatter plot the Blue describes the faulty data and Orange describes the healthy data. For plotting the scatter plot two variables are used PWM and Speed. The X-axis represent the PWM and The Y-axis represent the Speed. A confusion Matrix is also obtained for the trained data as shown in fig 7.

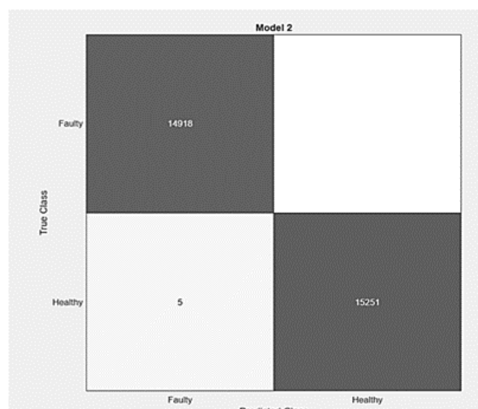


Figure 7: Confusion Matrix of Trained Data

Next, the trained model is exported to the MATLAB for further experiment. The trained model is used to classify the real time test data which we are collecting after deploying the DC motor control kit on-board. Below figure shows blocks of the On-board connection as shown in fig 8.

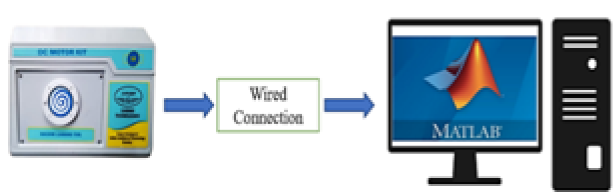
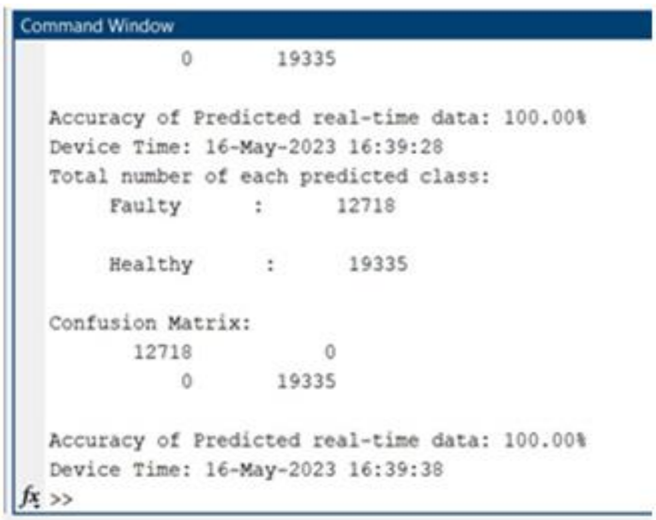


Figure 8: On-Board Connection

The Real time data is collected from the dc motor control kit for testing. The data is collected for similar PWM values which were used for training the machine learning model. The New real time data is stored into the excel file and that excel file is used to predict and classify the faulty data and healthy data.

D. RESULTS

The results are shown in the command which states the number of predicted values of each class and also gives the exact numbers of healthy and faulty data. It also generates the scatter plot fig 10 and confusion matrix for the testing data after the prediction is made. The accuracy of prediction is >95% as shown in fig 9.



```
Command Window
         0      19335

Accuracy of Predicted real-time data: 100.00%
Device Time: 16-May-2023 16:39:28
Total number of each predicted class:
     Faulty     :      12718

     Healthy     :      19335

Confusion Matrix:
       12718           0
           0       19335

Accuracy of Predicted real-time data: 100.00%
Device Time: 16-May-2023 16:39:38
fx >>
```

Figure 9: Result in Command Window (MATLAB)

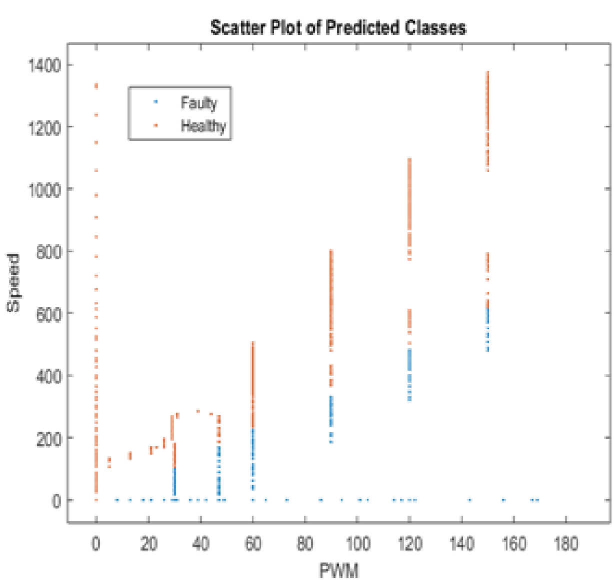


Figure 10: Scatter Plot of Testing Data

V. CONCLUSION

In conclusion, implementing Support Vector Machines (SVM) in the Classification Learner App in MATLAB, as well as predictive maintenance, to improve the performance of DC motors is a viable strategy. It is feasible to accurately detect and classify probable defects in the system by collecting data from the motor kit and applying machine learning techniques. This method can assist in identifying and addressing faults before they cause unexpected downtime or motor failure, resulting in cost savings and better operational efficiency. MATLAB and its Classification Learner App provide a simple and powerful platform for constructing and deploying machine learning models for fault detection and classification. Overall, this method has the potential to transform how industries handle maintenance and can help ensure that critical equipment, such as DC motors, performs optimally.

VI. ACKNOWLEDGMENT

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