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# Digitization of Real-Time Predictive Maintenance for High Speed Machine Equipment

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**Abstract:** In the recent decade, state-of-the-art techniques of maintenance in manufacturing firms have evolved. Redefining itself to come up with a whole new perspective by including a regime of digitization. From inter-compatibility to intra-network communication between hardware to highly interactive user interfaces have made the managing of necessary procedures extremely transparent. Even complex inclusions are easy to monitor following the current trends and digital transformation. Data generated through sources is big and unmanageable with a lack of filtering technologies to identify useful processable content. The proposed framework helps notify end-users by monitoring and identifying certain user-based settings and business functions. Suggested findings used machine learning (ML) algorithms surpass any previous claimed results. The modeling approach ensures consistent and reliable performance. Inclusive integration of notifying tools into trending smart devices has been tested and validated in this study. The coupling of multidiscipline open-source web-based technologies with minimum expense has been in focus for designing such applications. The best-identified set of tools that help enable the management of workflow multitasks, and their semantic arrangement through the latest state-of-the-art and scientific tools for generic work environments is covered in this study.

**Keywords:** Predictive Maintenance, Condition Monitoring, Machine learning, Random Forest Regression, Applications.

## 1 Introduction:

Key management of core technical challenges and administrative issues during the action of the work life cycle in an organization to retain and restore original efficiency and functioning of the holistic system is termed Maintenance. Recently startups have shown up providing maintenance support and services in a more accessible way, therefore, making them among the best, and most coveted subjects in modern business ventures. One viable method to improve maintenance efficiency without compromising quality is condition-based maintenance (CBM). In the past, this has mainly been achieved by utilizing the expertise and know-how of personnel gathered by training as well as long years of servicing the equipment. The downside of this ap-

proach is the dependence on a stable workforce with low fluctuation, which is often difficult to maintain in service projects. Furthermore, the results are often subjective depending on the experience level and interpretation of conditions by experts therefore mostly unreliable.

Vibration signals provide valuable information about the insights of the equipment on the operating condition. The presence of a fault can be detected by inspecting the vibration signal; also, it can localize the position of the fault and the health state of the equipment. Vibration signals can be captured through vibration sensors (e.g.; displacement sensors, velocity sensors, and accelerometers).

Sensitiveness of sensor for displacement measurement is highly sensitive in the low-frequency range ( $\sim < 1$  kHz), likewise, a flat amplitude response is more effective for velocity sensors within the range of 2 to 10 kHz. On the contrary, accelerometers come up with the best amplitude performance in a high range of frequency (i.e. Tens of kHz). This paper focuses on predictive maintenance by using vibration signals from the wireless vibration and temperature measuring sensors to reduce downtime and improve productivity and monitoring. The remainder of this paper is organized as follows. In Section 2, the related literature is reviewed. In section 3, we described the challenges in predictive maintenance. In sections 4 and 5, solution methodologies and their results are explained. Finally, the conclusions and possible future research directions are exposed in Section 6.

## **2 Literature Review:**

Fault detection of the rotating machinery can be identifying by the fault diagnosis technique, which can also be applied to get the details regarding about equipment's operating condition [1]. The rudimentary aim of the diagnosis for fault are mentioned as: (i) measuring and analyzing real time health of the equipment's (ii) determining reason behind breakdown or equipment failure and (iii) anticipating fault by developed in the modeled line and its trend [2]. Vibration signals of the machine can offer an early warning to the operator to make a crucial decision before any major failure or break down and reduce the unscheduled downtime. Vibration signal amplitude portrays basic image of the challenging problem, whilst frequency can give us some information about the source of the defect [3]. Condition Monitoring (CM) is used to provide alarms and actions to prevent production of out-of-specification components and avoid to machine breakdowns. Also, it is defined as a process of monitoring a parameter, which is indicative for a significant change of a developing failure of condition in machinery [4]. To avoid break down and preventing unexpected system downtime [5][6][7], CM can estimate the remaining useful life of the equipment. Predictive Maintenance (PdM) is aimed to determine the equipment working condition. Other than replacing the equipment at frequently intervals, PdM allows real-time evaluation and close monitoring of the equipment's, to alert the system administrator with replacement and servicing suggestions when the equipment is about to malfunction or fail [8]. PdM brings cost saving in the industries, since the requirement of PdM is based on the actuality, rather than estimating the condition of the machine's equip-

ment and its performance [9]. In the existing architectures GE digital Discrete Manufacturing Software, Manufacturing Execution Systems (MES) (such as ABB discrete manufacturing operations management software, SAP MES, Siemens SIMATIC IT for Discrete Manufacturing) demands new processing and analysis techniques for PdM with vibration sensor data.

Jemielniak summarized the signal processing techniques and collated advanced signal analysis techniques, the filtering (low-pass, high-pass and band-pass), averaging and RMS are the most effective [10]. Chimentinl et al. worked on the early detection methods for fatigue measurement of ball bearings using adaptive wavelet analysis [11]. Computational intelligence methods include evolutionary method like Genetic Algorithm (GA) [12], Artificial Neural Network (NN) [13], support vector machine (SVM) [14] and one-class SVM [15] have been effectively in machines for automatic detection and identification of faults.

### **3 Problem Statement:**

Global challenges and intense competitiveness in the markets recently rising steadily to attain peak. The firms are under constant pressure and in regular need to adapt recent advances for increasing efficiency, delivering better solutions, reduction in costs, and finally accepting digital transformation to capture inherited benefits to leverage technology to enhance management.

Real-time condition monitoring of machinery is a pivotal technique for guaranteeing the efficiency and quality of any production process. It may cost a big capital for the company in case of system failure. So, future prediction of the machine failure in advance and choosing desired alternatives, before the failure happens, is an essential precaution. At the operating time, most of the machines will vibrate and vibration has a strong relationship with the condition of the equipment or spare parts of the machine. Our main focus is predictive maintenance on high-speed rotating machinery such as wind turbines, baggage handling systems in the airport terminal. Experiencing digital transformation in real the data generated drives applications of artificial intelligence (AI) and big data shape our daily lives and decrease the intricacies of working processes in all sectors of industry and other important fields.

In this era, disruptive technologies play a crucial role in innovation, sensors harness invaluable analogous signals present from all around and all forms of physicality in nature. Mobile phones, wearable, smart devices, etc. are an essential part of daily life. Ever since the inception of these gadgets have formed an integral part of the human lifestyle and the average daily time humans remain engaged dealing with this electronical hardware is remarkably high. The purpose of this approach highlighting user-friendliness and inbuilt features of such tangible assets. Features such as touch interfacing, high-definition sensitive screens, high-quality compact processor and ram, etc. are all packed in with wireless connectivity. High-end interfacing is yet not been able to drive heavy machines and power electronics easily. This makes it an engineering problem of interdisciplinary approach as it remains untouched due to unfilled research gaps. While data is being collected more rapidly, the identification

and inter-compatibility of already evolved technologies and software are still not known. The skills needed in the development of merging technologies and decipher inter-compatibility are tried to be resolved in this paper using machine learning framework, application open-source platform, and recent advances in interfacing.

The core objective of this paper is to create a dashboard that helps managers to predict machine equipment failure in advance and according to that schedule maintenance activity. Also, we can achieve maximum productivity by minimizing downtime of the machinery equipment, and parallel it will reduce maintenance cost as well as labor cost.

## **4 Solution Approach:**

A generic framework comprising of IoT integrated auxiliaries with external systems is the demand of the times in the current domain. With an integrated and real-time data cascading, monitoring, streaming anticipatory model. The system would able to diagnose breakdowns, trigger alerts using simple logical rules (like ladder logic), and alarm authorized officials to execute intelligent decisions manually or automatically in real-time with all necessary safety guidelines and improvised compulsory regulations.

In this study, the infrastructure with embedded sensors and gateways, the buffering of all information flow from the production lines constantly integrating system and allowing accessibility to the components prior to developing the predictive maintenance system is assumed available. To enable communication between machines, collect data from devices, monitor live data, and manage historical data in enhanced view with suitable use of machine learning and AI techniques using the suitable platform is provided in this study. Collected data by devices from locations, with the least data dissipation, is offered, and the data from all sensors are processed in lesser time than usual to evaluate essential decisive actions within time boundaries.

### **4.1 Proposed Model:**

The proposed approach is a case study in the industrial environment to introduce signal processing techniques (time domain, frequency domain) that provides useful information to discriminant faults according to their installed position. The novelty of the work is to condition monitoring of spare parts of the equipment in high-speed machinery and estimate the remaining useful life of the equipment by using raw vibration data collected from the sensor installed in the machine equipment (Fig 1). Sensors are communicating with the data acquisition system (DAQ) to the base station and through edge computer raw data was stored in the cloud by using python programming. Then feature extraction and data filtering is applied to get processed data. There after compile processed data with historical maintenance data and train by using random forest algorithm. Finally, for the new data we predict machine equipment conditions in advance. This prediction can be monitored by the managers in computer system, smart phone, and smart watch.

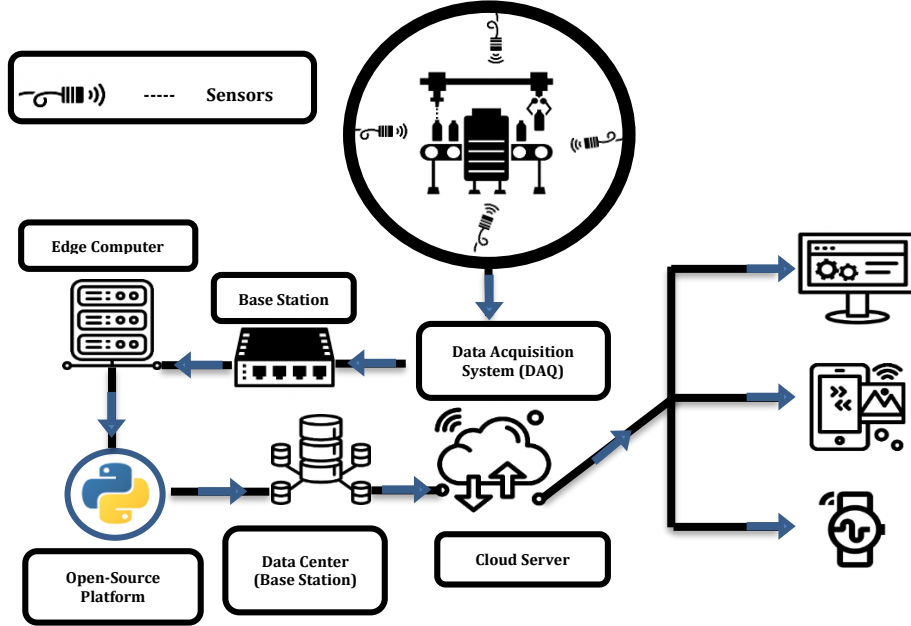


Fig.1. Digitization of predictive maintenance

#### 4.2 Data Collection:

Within this research we monitored machine equipment by using 18 wireless, temperature, velocity and vibration capturing sensors. Vibration data from several month of recording were collected from the sensors by using python language through edge computer and store them in the cloud so that in future space complexity would not be an issue. Raw data are stored in the form of temperature, acceleration (with respect to X-axis, Y-axis, Z-axis), velocity (with respect to X-axis, Y-axis, Z-axis).

#### 4.3 Feature Extraction:

Feature extraction can be divided into time domain analysis and frequency domain analysis. We extract mean (equation 1), RMS (equation 2), peak-to-peak (Fig 2), standard deviation (equation 3), kurtosis (equation 4), and Skewness (equation 5) to analyze time domain features. Also, apply FFT and IFFT filter out raw data.

$$Mean, \mu = \frac{1}{N} \sum_{i=1}^N x_i \quad (1)$$

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (2)$$

$$\sigma = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2 \quad (3)$$

$$x_{kurt} = \frac{1}{N\sigma^4} \sum_{i=1}^N (x_i - \mu)^4 \quad (4)$$

$$\tilde{\mu}_3 = E \left[ \left( \frac{x - \mu}{\sigma} \right)^3 \right] = \frac{E[X^3] - 3\mu\sigma^2 - \mu^3}{\sigma^3} \quad (5)$$

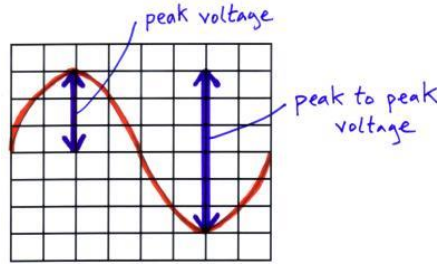


Fig.2. Peak-to-peak

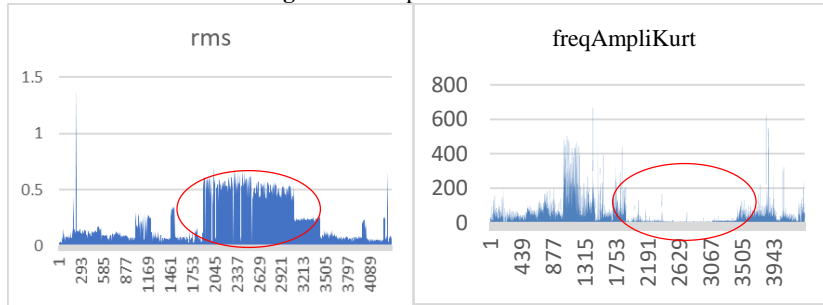


Fig.3. High rms value in idle time

Fig.4. Low kurtosis value in idle time

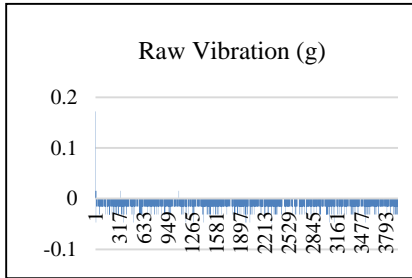


Fig.5. Low rms with low kurtosis in idle time

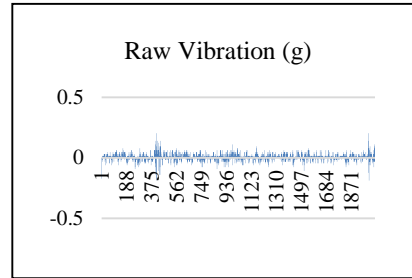


Fig.6. Low rms value in working condition

#### 4.4 Data Filtering:

Based on the experimental work, the vibration input can be divided into idle condition and working condition. Since idle time data has no impact in fault prediction, it is better to remove idle time data. We observed that idle time data has high rms (Fig 3) and low kurtosis (Fig 4) value. Therefore, it is better to remove vibration data with

rms value greater than 0.4 g and as well as low kurtosis value less than 25 (since it is noted that sometime low rms can be recorded in idle machine condition (Fig 5)). Therefore, we use only data generated in working condition of a machine i.e.; with low rms and high kurtosis (Fig 6). Also noticed that there are some gravitational effects (Fig 7) on the sensors and it will impact on the dataset. To overcome this issue, we use FFT and IFFT for further filtering of the data.

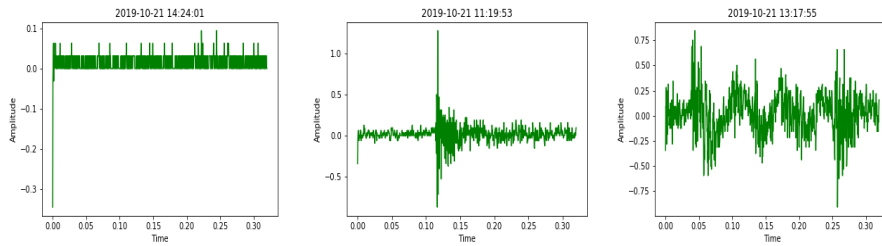


Fig.7. Gravitational effects and some external effects in reading

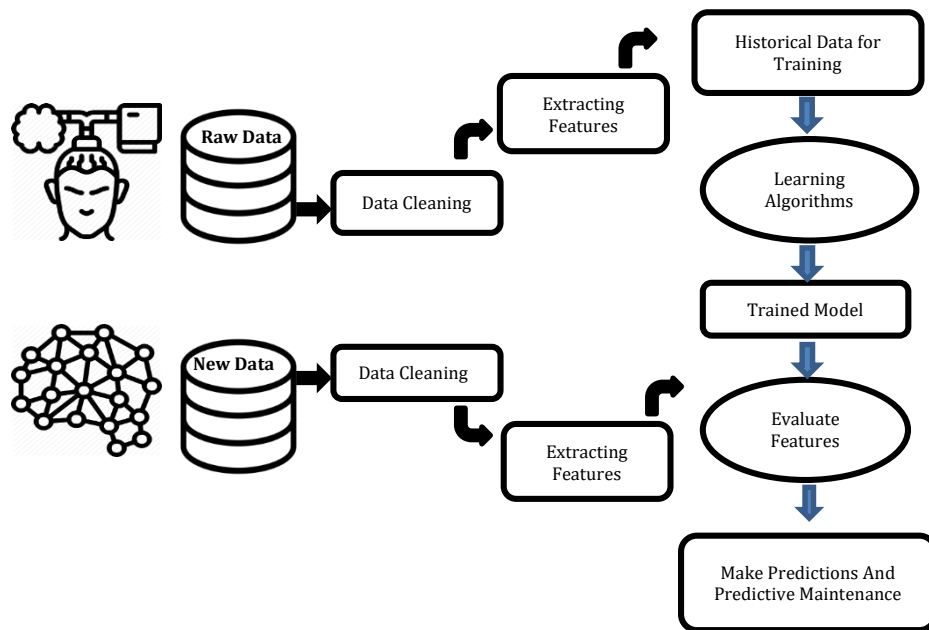


Fig.8. Prediction model by using historical maintenance data

#### 4.5 ML algorithm and Predictions:

To predict machine conditions in advance, we arrange historical maintenance data and processed data collected from sensors and use Random Forest (RF) as a supervised machine learning algorithm to train and validate our model.



Predictive models are generated using RF. Multiple randomized decision trees (DT) generates “forest” (ensemble) while simple average predictions get aggregated with RF. With an increase in the count of variables than the observations and sample performance are enhanced. RF is both classification and regression performing supervised machine learning. This work proposes an improvement where monitoring of machine equipment conditions is achieved. To attain this, data of status (activated and deactivated alarms) and data of operations (about historical maintenance) are employed to articulate the model. Work contributions include speed in processing of collected inputs, automation scalability, expansion, and economics. Results show predictive accuracy improvement of 94.7%, compared to the previous historical data. For real-time monitoring, currently, processed data is used for prediction by using the same trained algorithm.

## **5 Results and discussion:**

Opensource interfacing libraries for sensing analog signals and prediction using ML libraries when coupled have shown potential for the development of highly sensitive, inter-compatible, customizable, real-time, web-based tools. Nevertheless, intranet practices do not have security concerns. The analysis and post-processing of ML algorithms performed over edge cloud reflected highly efficient graphs, metrics, with substantial user control and full web ergonomics. Ergonomics for web development has also shown the potential of learning using ML based on customer preference. The suggested framework was tested twice using simulations and once a perturbation was mimicked to create a need disruption to invoke resilience procedure. The outcome has substantial deliverables as prediction graph as bad percentage showed in figure 8 by using python in the cloud and can display in desktop, smartphone as well as a smart-watch.

## **6 Conclusion and Future scope:**

A real time vibration-based fault detection using ML techniques was introduced in this study. This method used the vibration sensors attached to the machine parts to obtain the vibration data, which was processed, complied with historical maintenance data and then fed to the ML decision-making models. The ML techniques used is RF algorithm and this will make a real-time decision whether the machine or its equipment’s are safe to operate or not, which can be monitored using a smartphone. However, these findings are only based on indoor testing and for that it is not required to go infield for engineers to check machine conditions. Though sensor installation is costly, but by predicting machine failure in advance company can minimize machine downtime, labor hour and can increase productivity. In future sensor fusion can be used to minimize the overall cost of the entire system by minimizing the number of sensor and cost of the down time of the system.

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