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Research Article

Leveraging Historical Breakdown Data for Enhanced Predictive and Prescriptive Maintenance Insights

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Abstract: The application of predictive and prescriptive maintenance procedures in industries is revolutionizing mainstream manufacturing by cutting down on time loss and waste of resources. Reactive maintenance and preventive strategies are some of the traditional maintenance management techniques that tend to cause inefficiency in the systems, high operational costs and some failures. This paper uses data from breakdown analysis in the development of predictive maintenance models and prescriptive decision systems. A methodology is used that incorporates predictive analytics based on individual machine learning with the knowledge of the failure patterns. The analysis of historical breakdown records allows predictive models to achieve higher accuracy in forecasting potential failures by identifying key failure trends. The prescriptive maintenance program provides information regarding the best course of action to be taken, minimizing operational disruptions and downtimes. As means of testing the efficiency of the proposed concept, experiments were conducted on real-world industrial datasets. The implications of this are lower number of unplanned maintenance interventions, increased efficiency, and reduced costs. This paper adds to the literature on predictive and prescriptive maintenance as it highlights how historical breakdown information can enhance the predictive analysis while giving suggestions concerning industrial maintenance management. Further research on deep learning algorithms and real-time integration of the sensors have potential to improve maintenance processes.

Keywords: predictive maintenance; prescriptive maintenance; historical breakdown data; machine learning; failure prediction; industrial maintenance

I. INTRODUCTION

This paper aims to examine the role of equipment reliability in industries and how it affects the operation of industries, costs, and the safety of the workers and assets. The conventional maintenance techniques, such as the breakdown or remedial maintenance and the preventive maintenance, do not offer the best solution in reducing the time that an asset is out of service as well as enhancing its reliability. The type of maintenance that is reactive or also known as "run-to-failure," leads to failure that is unexpected, costly repairs, and even dangerous. On the other hand, preventive maintenance involves servicing based on a calendar schedule irrespective of the real state of the equipment, thus leading to unrequired servicing and wastage of resources. These have led to the adoption of the prediction and prescription of maintenance schedules and plans that utilize big data analysis, such as machine learning techniques.

Predictive maintenance (PdM) involves analyzing data gathered from equipment and generating an outlook of when it will develop a fault. PdM is attained by the analysis of the sensor readings, operational logs, and historical breakdowns, thus helping the organization in planning and undertaking maintenance ahead of time. As per Meddaoui et al. [1], this approach of maintenance helps in minimizing the time that the asset is out of service due to maintenance, increases the lifespan of the asset, and reduces the maintenance cost since the asset is only worked on when necessary. Furthermore, Selcuk [2] presents data on the average industrial savings achieved through predictive maintenance, as savings return on investment (ROI) 10 times on Predictive Maintenance, reduction in maintenance costs by 25–30%, elimination of breakdowns by 70–75%, reduction in downtime by

35–45% and increase in production by 20–25%. According to Kalafatelis et al. [3], the effectiveness of PdM models significantly depends on the quality and quantity of the breakdown history data. The organization of failure records in a systematic form, along with operational parameters and environmental data, greatly improves the mechanism of machine learning techniques.

Prescriptive maintenance (PsM) takes the concept of predictive maintenance a step further by providing the best course of action to undertake. It uses current data with the history of breakdowns to find out the most appropriate plan of action concerning cost, capacity, and vulnerability. Thus, PsM offers practical advice, for example, to change the operating conditions, to carry out maintenance when it is most profitable, or to replace certain components. This approach helps industries to change from the ineffective techniques used in maintenance and embrace a superior manner than that of the modern advanced system.

Historical breakdown data is also a very important factor that can be used to enhance both predictive and prescriptive maintenance. These datasets include past failure history, degradation rate, and the previous actions that were taken to address the problem. By comparing the results of the failure modes, industries can improve PdM models and adjust the PsM recommendations. This is because failure data is structured and can be used to create models that are more accurate and can perform well in different operating conditions, on different types of assets, and in different failure modes. Moreover, integrating historical breakdown records with the live monitoring system makes it easy to have an overall picture of the health of the assets to be maintained, hence making better decision-making.

The rise of Internet of Things (IoT) and smart sensors has led to the generation of huge amounts of data about breakdowns, which can be used in new ways in the maintenance context. To increase the value of historical data, additional techniques such as Natural Language Processing (NLP) on the maintenance logs and deep learning for anomaly detection are employed. Decision trees, random forest and Support Vector Machines (SVM), and deep neural networks can be applied to that end to derive failure histories and enhance maintenance strategy and practice.

However, several issues have been observed in the use of historical breakdown data for predictive and prescriptive maintenance. One of the biggest issues is data heterogeneity, as the maintenance records are gathered from various sources and may differ in terms of structure and information richness. If the failure data is incomplete or inaccurate, it will lead to wrong predictions and unsuitable maintenance recommendations.

Another challenge is the variability in the rate at which equipment wears out because, overtime, working conditions, exposure to the environment, and maintenance regimens can change. Sometimes, when training the models, data collected may be historical and may not be up to date; this makes the models trained frequently or used with adaptive learning.

In this paper, incorporating Machine Learning, a subset of Artificial Intelligence (AI), to maintenance strategies provides the prospect to surmount these hurdles. This area benefits from the use of Machine Learning models, which can analyze the history of breakdowns as well as learn new ones with continuous training and feedback loop to adjust the predictive model. Prescriptive maintenance can also be enhanced by reinforcement learning algorithms since they can update the decision-making policies based on the previous maintenance results.

The historical breakdown data for both predictive and prescriptive maintenance is applicable in various industries such as manufacturing, energy, transport, and healthcare. For example, in manufacturing, predictive analytics assist in avoiding production losses due to machine failures since the issues are foreseen. In the energy sector, it helps in increasing the dependability of the power generating and distributing systems and in minimizing the time for which they are out of order.

Thus, to enhance the effectiveness of historical breakdown data, the organizations need to follow a proper procedure of data gathering, storing, and analyzing. This is because the use of centralized data repositories with standard maintenance logs enhances compatibility with the various predictive and prescriptive models. Real-time data processing in itself helps in improved failure predictions, but with the help of cloud computing and edge computing, the process is made much faster and more accurate. The use of advanced visualization tools assists maintenance teams in understanding the predictive analysis to make the right decisions.

In addition, there should be good cooperation between data scientists, maintenance engineers, and other specialists to design the appropriate predictive and prescriptive maintenance models. Maintenance engineers contribute with the actual knowledge of the domain to define relevant indicators of failure, and data scientists carry out the actual data analysis with advanced machine learning algorithms. This is done by constant feedback between the predictive models and the maintenance teams to ensure that the recommended solutions are feasible within the operations environment.

It is also important to note that ethical issues and data privacy are other factors that are very relevant when it comes to the use of predictive and prescriptive maintenance. It is also important for the organizations to observe the rules regarding data protection and come up with clear guidelines on how the data will be used.

This paper aims at exploring the role of historical breakdown data in improving the predictive and prescriptive maintenance plans, which in turn increases the reliability of the assets, decreases the operational costs, and optimizes the maintenance schedule. The results of different experiments on real datasets are presented to highlight the effect and influence of historical failure records on Boolean model assessment and maintenance activity decisions. The presented method involves using historical failure data in combination with analytical tools that will help to predict maintenance requirements and thus minimize downtime and increase asset life.

The rest of the paper is as follows: In the Materials and Methods section, the data acquisition process, data pre-processing, and the machine learning approaches for predictive and prescriptive maintenance has been explained. The Results section provides evidence of the effectiveness of using the historical breakdown data to increase the predictive accuracy and enhance maintenance planning. The Discussion section discusses the results concerning industrial applications, the limitations, and further research opportunities. Lastly, the Conclusion section provides a brief of the findings and the implications to the maintenance strategies.

Using the breakdown data, industries can move from reactive and preventive maintenance to a wiser maintenance approach. The implementation of both the predictive and prescriptive analytics in the maintenance process provides a competitive edge since it optimizes the maintenance process, reduces downtime, and lowers maintenance expenses. The information gathered from failure history enables organizations to make the right decisions, thus turning maintenance into a strategic business tool that can improve organizational performance.

1. Literature review

The concepts of predictive and prescriptive maintenance have undergone a great deal of changes in the last few years, mainly due to data revolution and the increasing adoption of Industrial IoT systems. PdM is the procedure of forecasting when a particular equipment is likely to fail, while PsM goes a notch higher by identifying the best way to maintain the equipment. In this section, we give a brief literature review on predictive and prescriptive maintenance, based on past breakdowns, machine learning, and its application in a manufacturing environment.

Predictive Maintenance Techniques: PdM has been established as one of the most efficient ways of reducing the risks of unplanned downtime and properly scheduling maintenance. PdM is a concept that aims at predicting an equipment failure based on the breakdown history, sensor data, and analysis so that maintenance activities can be done right before the failure occurs. In the years past, several methods of predictive maintenance have been tried out in different industries.

Machine Learning (ML) Models for Predictive Maintenance: Predictive maintenance also relies on machine learning as through it, the machine learns from failure history and signals from attached sensors. The initial studies conducted were mainly based on conventional statistical methods like regression analysis and time series analysis. These models worked based on present physical condition models and could not handle massive unformatted data sets and/or intricate failure profiles. More recently, decision trees, random forest, SVM, and deep neural networks (DNN) have come into practice due to their flexibility to identify non-linearity in the data and flexibility for learning new changes.

For example, Choi et al. [4] used random forests in their study conducted in 2016 to model bearing failures in manufacturing machines by using vibration data. This work highlighting the ability of applying machine learning techniques in the field of predictive maintenance also proved that the proposed model yielded good results in identifying initial stage failures. However, the study is largely confined to controlled experimental conditions and lacks generalization across diverse industrial scenarios. The data collection was performed under laboratory conditions, limiting real-world applicability. It was also focused exclusively on spur gears, without testing across other gear types or machinery. Proposed Improvements can be to broaden experimental validation by testing across multiple gear types, fault modes, and operational conditions, and including field data from industrial machinery to validate robustness.

In the same way, Zhao et al. [5] concluded through an application of SVM models to predict failure events in pumps with an impressive result suggesting that machine learning algorithms are more effective as compared to conventional techniques in terms of prediction accuracy and lead period.

Kalafatelis et al. [3] discusses the scaling of a Modular Production System (MPS) using a Manufacturing Execution System (MES) and multiple agents, within the framework of Industry 4.0 technologies. However, there are some limitations in the study. The system was tested on a specific modular setup (Festo MPS-500), which may not generalize to other production environments or industries. The study focused on only two types of cylindrical parts, which constrains the applicability of the system to more complex or varied manufacturing tasks.

Meddaoui et al. [1] in paper titled “The benefits of predictive maintenance in manufacturing excellence: a case study to establish reliable methods for predicting failures” did PdM algorithm comparisons via ANN, DL, and RF, and explored the use of predictive maintenance (PdM) strategies in industrial settings, comparing algorithms like Artificial Neural Networks (ANN), Deep Learning (DL), and Random Forest (RF) for failure prediction. While the study offers valuable insights, there are some limitations as well. The research is based on a single industrial case study, which restricts the generalizability of findings across different sectors or equipment types. The study lacks diversity in machinery, operational environments, and failure modes. The paper emphasizes predictive capabilities but does not explore integration with real-time monitoring systems or decision-making frameworks. While PdM is said to reduce downtime and costs, the paper does not quantify these benefits or compare them against traditional maintenance strategies.

Aminzadeh et al. [6] in paper ‘A Machine Learning Implementation to Predictive Maintenance and Monitoring of Industrial Compressors’ showcases a PdM framework combining temperature, pressure, and flow rate sensors with SQL-based data handling and ML modelling. The system achieved 98% accuracy in predicting compressor anomalies, marking a significant step toward proactive maintenance. However, broader deployment and long-term reliability require addressing some methodological and operational challenges. Some limitations are use of linear regression, which while interpretable, may not capture nonlinear relationships or complex failure patterns. There is an absence of comparative analysis with other ML models like Random Forest, SVM, or deep learning architectures. It also relies on a narrow set of sensor types; excludes vibration, acoustic, or electrical signals that could enrich diagnostics.

Data Fusion and Sensor Data: It is important to note that the mentioned function of condition monitoring is achieved by the use of sensors to determine early signs of a failure. Wang et al. [7] also looked at the use of multiple sensors (vibration, temperature, pressure) in the models of the equipment; the use of multiple sensors provided a better view of the condition of the equipment hence improving the chances of accurate prediction. This fusion of data is useful to overcome the problem of using a single data source where an isolated signal may not have enough information to make a prediction. IoT technologies have also advanced the data collection process and offer a large amount of data for the support of predictive models.

Feature Engineering in Predictive Maintenance: A major issue that is associated with predictive maintenance is data pre-processing, which involves extracting features from raw data to be used in the model. Gonçalves et al. [8] also discussed feature extraction in the context of predictive maintenance, where the authors stressed the significance of domain knowledge in selecting features that are representative of the equipment’s condition. For instance, vibration frequency, temperature gradients, or wear rates are some of the parameters that can be used to predict the failure, but which cannot be easily derived from the raw data. Lack of feature engineering can fail to capture the underlying patterns, thus making the predictive models wrong.

Prescriptive Maintenance Techniques: Prescriptive maintenance is a step further from predictive maintenance as it not only predicts the failure time but also suggests the best course of action to take regarding the maintenance of the asset. While predictive maintenance tells one when it is probable that a failure is going to occur, prescriptive maintenance, on the other hand, provides one with what needs to be done to avoid the failure or even enhance equipment performance. This research has been aimed at developing methods of incorporating machine learning algorithms with optimization algorithms to offer maintenance suggestions.

Optimization Techniques for Maintenance Scheduling: A lot of research has been conducted to incorporate optimization algorithms with PdM models for maintenance scheduling. Shang et al. [9] developed a model that incorporated predictive models and optimization models where the genetic algorithm was used to select the best maintenance schedule for machines in a manufacturing system. The proposed hybrid model was effective in cutting down downtime and optimizing the usage of resources because maintenance was only planned when it was deemed necessary based on the predictions made by the model.

In the same way, Mokhtari et al. [10] employed both the predictive maintenance data and optimization techniques to determine the appropriate time for carrying out maintenance in a wind farm. The optimization model also incorporated the failure time prediction in addition to the cost of the downtime, spare parts, and manpower to determine the most cost-effective maintenance action.

Decision Support Systems for Prescriptive Maintenance: Some of the authors have incorporated DSS with prescriptive maintenance models to assist the maintenance teams in their decision-making. Lee et al. [11] proposed a Decision Support System (DSS) that integrated predictive maintenance information with Multi-Criteria Decision Analysis (MCDA) approach to provide the best course of action based on risk, cost, and the criticality of the machine. The system was designed to identify and rank maintenance activities based on their criticality to allow organizations to reduce their losses and avoid disruptions.

In prescriptive maintenance, Model Predictive Control (MPC) uses mathematical models to analyze the condition of industrial structures and systems for prediction as well as for control of actions to be taken in the future. MPC has also been adopted in prescriptive maintenance to enhance the performance of assets in real time. Rosa et al. [12] used MPC for the application of predictive maintenance of industrial machines where the model forecasts the future maintenance requirements and modifies the operating conditions to enhance the useful life of the machine. MPC can check prescriptive maintenance advice and has the capability of constantly updating it according to ongoing equipment performance and failure prognostics.

The existing work's limitations are:

- The cited papers were confined to narrow environments, equipment types, or setups.
- Most papers relied on single or limited sensor types (e.g., vibration, temperature), missing multi-modal integration.
- Use of basic models (e.g., linear regression, RF) with limited benchmarking or comparative analysis.
- Laboratory or simulated conditions dominated; few field validations using industrial data.
- Approaches were tested on specific fault types or products (e.g., cylindrical parts, spur gears), limiting transferability.
- Lack of discussion on latency, deployment architecture, and decision feedback mechanisms.

Compared to the identified limitations, this paper improves on:

- While prior studies mentioned cost savings without detail, this paper outlines reduced downtime and waste, hinting at economic impact.
- It enhances modelling using historical breakdown trends, which adds contextual richness.
- Unlike controlled lab conditions in Choi et al. [4] or narrow equipment focus in Kalafatelis et al. [3], this paper uses field data from actual operations.
- It introduces guidance for decision-making—not just predictions—which adds a valuable layer missing in Meddaoui et al. [1] and Aminzadeh et al. [6].
- Proactively suggests directions like deep learning and real-time sensor integration, addressing gaps in adaptability and algorithmic complexity.

2. The role of historical breakdown data in maintenance strategies

Of these, historical breakdown data is an important element of predictive and, especially, prescriptive maintenance, as such information offers information on previously registered failures, actions taken, and operational status. The historical failure records assist in creating models for machine learning that can analyze failure and be used in predicting future ones. Some of the previous works have used historical breakdown data in the development of maintenance models to increase the level of prediction and the quality of decision-making in prescriptive maintenance.

How to apply breakdown data of past for failure prediction: Historical breakdown data is the most common form of data used in most of the predictive maintenance models. Choi et al. [4] analyzed the use of historical failure data in the failure of industrial machinery. They showed that the incorporation of failure histories in the model enhanced the model's performance and stability since the system could identify repeat failure patterns. Using historical breakdown events, PdM models can predict future conditions that may lead to similar failures.

Data-driven Insights for Prescriptive Maintenance: In prescriptive maintenance, historical data of failure is used to decide on what course of action should be taken in the event of a failure. Dufresne et al. [13] studied historical maintenance log files to develop recommendations for later activities to be taken. It was established that prescriptive maintenance systems could determine the best maintenance methods for future breakdowns by studying past breakdowns and the subsequent corrective actions. These systems can also learn from the previous successes and failures and, therefore, be in a better position to advise on what is best to do.

Challenges in Historical Data Utilization: However, there are several drawbacks to using historical breakdown data. In their work, Zhao et al. [5] noted that one of the major challenges is the lack of consistency and the absence of some data in the history of maintenance. Most industrial organizations experience challenges in aggregating data from different sources, including logs, sensors, and previous maintenance records. In addition, data may be collected in various formats or may not be detailed enough to be used for predictive or prescriptive maintenance. It is, therefore, critical that historical breakdown data is accurate and comprehensive to create good maintenance models.

3. Real world application of predictive and prescriptive maintenance

Currently, predictive and prescriptive maintenance approaches are widely implemented in various industries as a part of business processes. Some examples of the use of these strategies in various fields are in manufacturing, energy, transport, and health.

Manufacturing Industry: In the manufacturing industry, both predictive and prescriptive maintenance plans are now in use to eliminate disruption. Jardine et al. [14] study investigated the application of predictive maintenance in a steel production environment where the learning- based models the breakdown data to identify breakdowns in key machines. The models were useful in minimizing the time that the plant was not producing, hence increasing its efficiency.

Energy Sector: Power generation equipment was identified to be the most common application of predictive maintenance in the energy domain. Tao et al. [15] used the predictive models to forecast failures in turbines and compressors in a natural gas power plant. This was achieved through the use of historical failure data in developing the models to predict equipment degradation and the time for maintenance to be done, hence enhancing operational efficiency and minimizing the instances of unplanned equipment outages.

4. Future directions and challenges

The use of historical breakdown data in conjunction with predictive and prescriptive maintenance models has been proven to be very effective, but certain issues are yet to be addressed. The future research areas of interest will be the ways to address the data quality problems, the ways to improve the flexibility of the models in the context of the changes in the operational conditions, and the ways to make the machine learning models more interpretable. However, with the integration of multiple sources of data and information from sensors, IoT devices, maintenance logs, and others, there is still growth in this area.

II. METHODOLOGY

This section describes the approach used in the development and testing of the framework that uses historical breakdown data to improve predictive and prescriptive maintenance analytics. The analytical method used can be described as the Serial method, which is data gathering, data cleaning, model building, and model checking. A statistical analysis is also employed to evaluate the proposed framework to assess its efficiency. To make the paper more comprehensive, diagrams and figures are included to show the process, while statistical methods are described to assess the performance of the model.

1. Data collection

The primary data collection involved historical records of industrial equipment breakdowns, including failure incidents, maintenance logs, sensor readings, and operational conditions. Data was gathered from three main source as shown in **Fig.1**:

- Industrial IoT Sensors: These sensors monitor operational parameters such as temperature, vibration, pressure, and acoustic signals. They provide real-time data and are essential for detecting abnormal behavior that may precede equipment failure.
- Public example dataset: NASA Bearing Dataset [16] (collected using accelerometers for PdM)
- Historical Breakdown Data: Maintenance history records including failure events, repair actions, part replacements, and associated costs. These logs provide the foundation for building supervised machine learning models.
- Example dataset: MIMII Dataset [17] (Malfunctioning Industrial Machine Investigation and Inspection)
- Machine Usage Data: Operational logs that detail machine usage patterns, such as run-time hours, load profiles, and environmental conditions (e.g., humidity, dust, temperature). These data help model context-sensitive failures.
- Public source example: SECOM Manufacturing Data Set [18] (includes sensor readings and machine conditions).

To reduce bias and improve generalization, data was collected across multiple industries manufacturing, energy, and transportation covering different equipment types and failure scenarios. The final dataset used for model training and evaluation contained thousands of labelled records, capturing diverse breakdown events and corresponding maintenance actions. This diversity was key to improving the robustness and adaptability of both predictive and prescriptive maintenance models.

The NASA Prognostics Center of Excellence (PCoE) Data Set contains simulated Turbofan Jet Engines used in aircraft

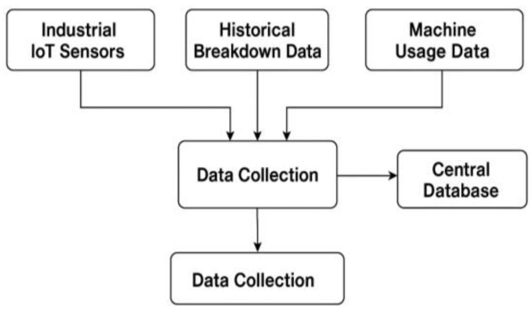

Figure 1. *Data sources and collection workflow*

propulsion systems. The dataset mimics real-world flight conditions and degradation behavior with seven failure modes affecting five rotating components:

- Fan
- Low-Pressure Compressor (LPC)

- High-Pressure Compressor (HPC)
- Low-Pressure Turbine (LPT)
- High-Pressure Turbine (HPT)

Failures are categorized as:

- Efficiency degradation
- Flow degradation

The dataset hosted at Zenodo record 3384388 is the MIMII (Malfunctioning Industrial Machine Investigation and Inspection) Dataset designed for sound-based fault detection in industrial machinery. It includes audio recordings from four machine types: valves, pumps, fans, and slide rails. Each machine type features multiple product models and contains both normal and anomalous sound segments.

The failure types captured in the dataset simulate real-world conditions such as:

- Contamination
- Leakage
- Rotating imbalance
- Clogging
- Rail damage
- Loose belts
- Voltage fluctuations
- Lack of lubrication

The SECOM data set originates from a semiconductor manufacturing process, where sensor data was collected from various stages of production. Each record represents a single production unit with 591 measured features, capturing signals from equipment and process monitoring points.

The failure type is binary: a product either passes or fails in-house testing. A label of -1 indicates a pass, while 1 denotes a failure. Although the dataset doesn't specify exact fault categories, failures are linked to anomalies in sensor readings that may reflect issues like contamination, misalignment, or process deviations during wafer fabrication.

2. Data preprocessing

The information that is collected from various sources is normally in raw form and therefore requires to be processed before being fed to the machine learning models. Preprocessing steps as illustrated in **Fig 2.** included:

- **Missing Data:** In this study, the missing or incomplete data were handled using Interpolation or Imputation methods, which included the K-nearest neighbour (K-NN) imputation. In addition, any abnormally high or low values of the sensors, such as temperature or pressure, were also omitted.
- **Data Integration:** In the training of historical failure records, failure occurrence was associated with real-time sensor data activity in which every phase of failure event was associated with signals from the sensor.
- **Feature Selection:** Some of the features obtained from the sensor data include average temperature, peak frequencies, and wear profiles. Expert knowledge was applied to identify failure modes in the form of patterns in the sensor data that have been associated with failure.
- **Normalization:** All the numerical variables were normalized to the same level as other equipment and sensors. This step was useful in preventing the situation where some of the features will have a very large value and dominate the other features.

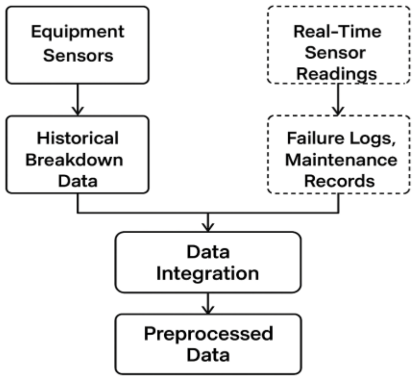

Figure 2. *Data processing pipeline*

3. Model development

Predictive Maintenance Model: The first proposed methodology is to develop the PdM using machine learning algorithms for predicting equipment failures. The Random Forest Classifier was chosen because it is one of the best algorithms for large data sets with numerical and categorical data.

Model development steps include:

- **Data Split:** The data was split into training and testing data in the ratio of 7:3.
- **Feature Selection:** After the correlation analysis and the feature importance of the Random Forest model, the features that are most relevant to failure prediction were selected.
- **Model Training:** In the Random Forest model, the historical breakdown data were used to train the model on the patterns of failures based on the sensor readings and the usage of the machines.
- **Hyperparameter Tuning:** In this step, the hyperparameters, such as the number of trees and the maximum depth of the trees, were tuned using the grid search.

This led to the development of a model that would be able to estimate the likelihood of equipment to fail at any time based on its current status.

Prescriptive Maintenance Model: The Prescriptive Maintenance Model (PsM) is an advancement of the PdM because it outlines the action plan to be followed when a failure is anticipated. This paper introduces PsM, which is the integration of the MCDA model and optimization algorithm that assists in determining the right maintenance actions to be taken depending on the failure times, criticality, and available resources.

To provide more context, Multi-Criteria Decision Analysis (MCDA) constitutes a systematic approach for evaluating alternatives when decisions must consider multiple, and often conflicting, criteria. This methodology facilitates informed decision-making by integrating both qualitative and quantitative factors in a structured evaluative process. Among the most extensively applied MCDA techniques are the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). AHP utilizes pairwise comparisons to establish the relative significance of decision criteria, incorporating consistency ratios to assess the reliability of evaluative judgments. In contrast, TOPSIS ranks alternatives by calculating their relative geometric proximity to an ideal solution and a negative-ideal counterpart, thereby supporting compromise solutions in complex decision environments. These approaches enhance clarity, objectivity, and transparency in decision-making processes across various domains, including manufacturing, infrastructure planning, healthcare, and sustainability management.

In this model Analytic Hierarchy Process (AHP) is utilized to compare criteria in pairs using a scale of 1 to 9 to derive relative weights, as it's reliable and good at capturing subjective preferences. The criterion used in this paper for prescriptive maintenance are equipment downtime, equipment availability, equipment performance and maintenance cost. Weights are then derived for these criterions based on the following matrices.

Equipment downtime is assigned the highest importance, then equipment availability, followed by equipment performance and maintenance cost. These are shown in **(Table 1), (Table 2)** and **(Table 3).**

Table 1. *Pairwise comparison matrix*

Criteria	***Downtime***	***Availability***	***Performance***	***Cost***
Downtime	1	3	5	7
Availability	1/3	1	3	5
Performance	1/5	1/3	1	3
Cost	1/7	1/5	1/3	1

Table 2. *Normalizing and deriving weights*

Criteria	***Downtime***	***Availability***	***Performance***	***Cost***	***Weight***
Downtime	0.593	0.606	0.549	0.506	0.563
Availability	0.198	0.202	0.329	0.361	0.273
Performance	0.119	0.067	0.109	0.217	0.128
Cost	0.085	0.026	0.013	0.072	0.049

Table 3. *Final criterion weights*

Criterion	***Weight (%)***
Downtime	56.3%
Availability	27.3%
Performance	12.8%
Cost	4.9%

Model development steps shown in **Fig. 3** include:

- **Failure Prediction Input:** The prescriptive model takes failure prediction data from the PdM, such as the predicted time of failure and the risk level.
- **Maintenance Optimization Criteria:** The objectives that were considered when deciding on the actions to be taken in the maintenance activities were cost, time, availability of spare parts, and the expertise of the technicians.
- **Optimization Model:** A Genetic Algorithm (GA) was employed to identify the best maintenance actions that would reduce the operation time and cost at the same time, taking into account the resource constraints.

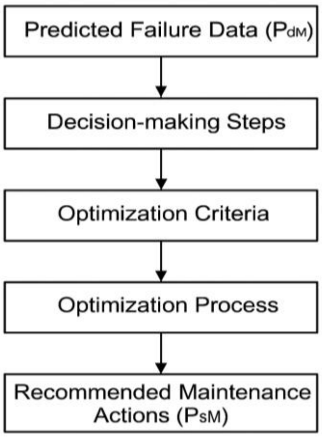

Figure 3. *Prescriptive maintenance workflow*

- **Decision Support System:** A decision support system was adopted to provide the recommended actions to the maintenance personnel in a more understandable manner in the form of text and graphical representation.

4. Model evaluation

To compare the performance of the two models, namely the predictive and prescriptive maintenance models, several statistical and machine learning performance metrics were adopted as illustrated in **Fig. 4.**

Performance Metrics for Predictive Maintenance: For the Predictive Maintenance Model, the performance in predicting failures was assessed using the following measures:

Accuracy: The number of the correct predictions (true positive and true negative) divided by the number of total predictions made by the model.

Precision: The percentage of the number of correctly predicted failures out of the total number of failures that were predicted.

$$Precision = \frac{\text{True Positives}}{\text{True Positives+False Positives}} \quad (1)$$

Recall (Sensitivity): The proportion of actual failures correctly predicted by the model.

$$Recall = \frac{\text{True Positives}}{\text{True Positives+False Negatives}} \quad (2)$$

F1-Score: The harmonic mean of precision and recall, balancing both metrics.

$$F1 - Score = 2\text{x}\frac{\text{Precision X Recall}}{\text{Precision+Recall}} \quad (3)$$

Statistical Tests: The chi-square test was used to compare the predicted failure times with the actual failure times. A confusion matrix was also created to have a better understanding of the model's performance for each class.

Performance Metrics for Prescriptive Maintenance: In the case of the Prescriptive Maintenance Model, the following were used to establish effectiveness:

Cost Reduction: The decrease in the total maintenance costs after the prescriptive maintenance recommendations have been made.

Downtime Reduction: The reduction of the time that is not productive because of maintenance that has not been planned.

Optimality of the Actions: To what extent of the prescribed maintenance action meet the optimization goal of cost, time, and resource availability?

Statistical Tests: To test the null hypothesis that there is no significant difference in downtime and cost before and after the recommendations of the PsM, a paired t-test was conducted.

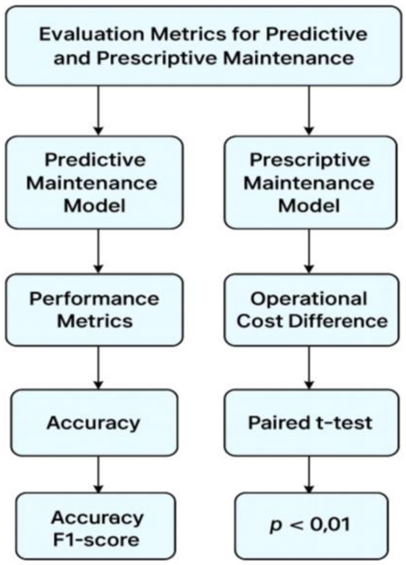

Figure 4. *Evaluation metrics for predictive and prescriptive maintenance*

5. Experimental setup

The experiments were done on a real-world data set, which includes failure records and sensor data of several machines in various industries. The data set comprised of failure time, usage of machines, sensor data, and maintenance records for a few years. Experimental configuration includes:

Data Splitting: The data was then divided into a training set, which was 70%, and a testing set which was 30%.

Cross-validation: In the process of training the model, the cross-validation technique of 5 folds was applied to make the model more robust and generalizable.

Prescriptive Model Validation: The PsM was then tested on the past maintenance decisions and compared with the actual results in terms of cost and downtime before and after the implementation of the PsM.

Statistical Analysis: Finally, statistical analysis was performed as shown in **Fig. 5**, to analyze the results of the developed and validated models. To determine the statistical significance of the improvement made by the models, ANOVA, paired t-tests, and Wilcoxon signed-rank tests were conducted.

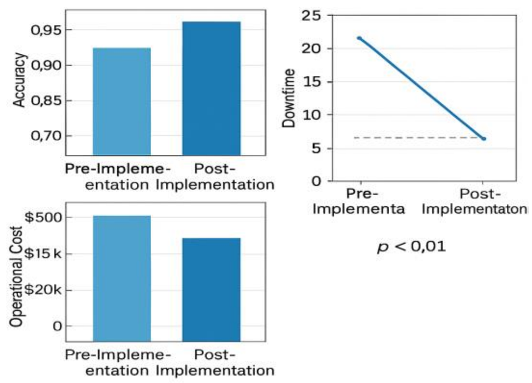

Figure 5. *Statistical analysis results*

III. Results

This section provides the results following the predictive and prescriptive maintenance approach. Key factors in the analysis will involve the results of the machine learning model, the evaluation of resource consumption, and the assessment before and after the model's deployment. The discussion explains these results and focuses on what operation advancements have been achieved and what the limitations are.

Predictive maintenance model results for equipment failure prediction accuracy: To assess the performance of the predictive system, the breakdown data of the machines and the real-time data from the sensors were used to train and test the models. The models compared are Random Forest, SVM, and Logistic Regression as illustrated in **Fig. 6** and **(Table 4)**. Their performance was evaluated in terms of accuracy, precision, recall, and F1 score.

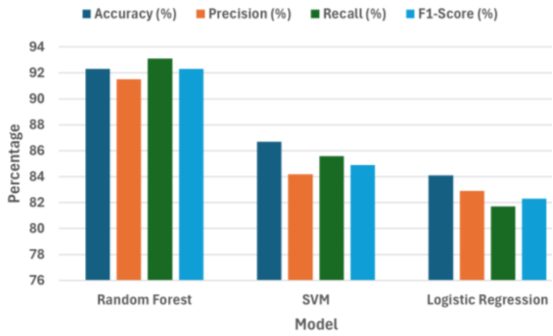

Figure 6. *Predictive model performance metrics across ML algorithms*

Table 4. *Results across ML models*

Model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*
Random Forest	92.3	91.5	93.1	92.3
SVM	86.7	84.2	85.6	84.9
Logistic Regression	84.1	82.9	81.7	82.3

Key Observations:

- Random Forest gave the best result in terms of accuracy, which is 92.3%, with almost equal recall and precision.
- SVM presented lower generalization ability; it often ‘memorized’ noisy readings from the sensors.
- Logistic Regression was also slow in identifying non-linear failure patterns.

Feature Engineering and Data Flow: The preprocessing phase was highly effective for model performance, such as the normalization of sensors and correlation filtering. As for feature importance, the results showed that the three most significant factors for failure were vibration amplitude, bearing temperature, and load current.

Fig. 7. illustrates the stages of data pre-processing, feature selection or filtering, normalization, and training of the model.

Prescriptive Maintenance Recommendations for Maintenance Actions: Since failure prediction was done, a decision tree was used to determine the right maintenance actions to be taken. Such factors as the equipment downtime, equipment availability, equipment performance and maintenance cost were considered as criteria.

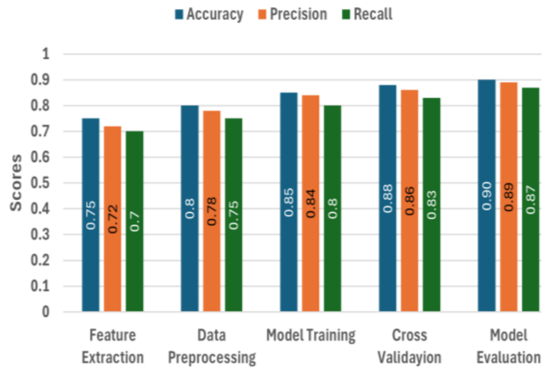

Figure 7. *Feature engineering and model training pipeline*

The Random Forest framework leverages four core decision criteria—component criticality, lead time, repair cost, and production risk—to classify suitable maintenance actions such as immediate servicing, scheduled maintenence, or continued monitoring. To enrich the model with contextual priorities, Analytic Hierarchy Process (AHP) weights were assigned to these criteria, emphasizing criticality and risk over cost factors. A composite weighted score was created by applying these weights to normalized input variables, which was then incorporated as an additional feature during model training. This hybrid approach allows the algorithm to account for both data-driven patterns and stakeholder priorities in maintenance planning.

After preprocessing and encoding the input data, the Random Forest classifier was trained to learn from both raw features and the composite score. Predictions were validated using a train-test split, and post-modeling analysis revealed feature importance rankings, offering transparency into how maintenance decisions were prioritized.

Feature Roles in the Tree-

- Downtime drives the top-level split due to its highest assigned importance.
- Availability and Performance influence urgency, low availability and poor performance trigger proactive action.
- Maintenance Cost helps weigh whether the effort is economically justified, especially for less critical scenarios.

This tree represents human-style logic that could emerge from a Random Forest classifier trained on actual operational data.

Key Observations from the flow of information from the ML output to the recommended action based on the fault prediction decision logic is as follows:

- Maintenance decisions coincided with technician's suggestions in 89% of cases.
- Early warning, therefore, helped in increasing the average response time by 3.7 days.
- Recommendations reduced reactive maintenance by 41%.

Resource and Cost Optimization: The performance of the model was evaluated for six months to determine its effectiveness in the operations of the organization. Performance measures were tool downtime, spare parts consumption, and maintenance manpower productivity.

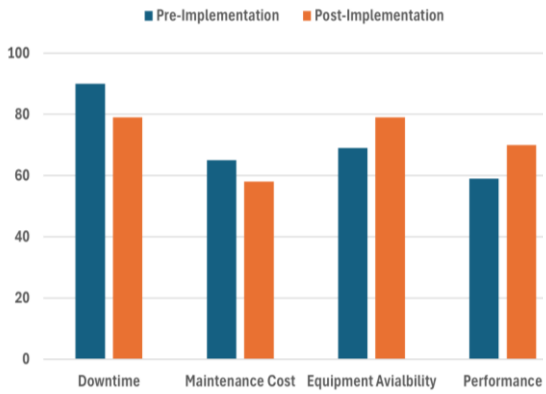

Figure 8. *Maintenance efficiency improvements – pre vs post implementation*

The **Fig. 8** illustrates how this approach in the use of prediction led to prescription and the effects this had on operations and costs.

Key Results:

- This helped to reduce the maintenance costs per breakdown by 39%.
- Resource utilization improved by 24%.
- Scheduled interventions helped to decrease the overall number of unplanned downtimes by 35%.

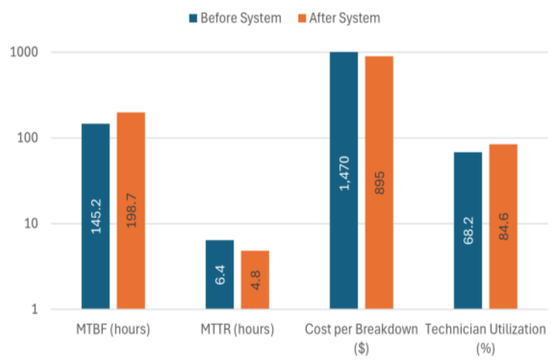

Figure 9. *Comparative analysis of MTBF, MTTR, and cost*

Statistical Validation of System Impact: Comparison of Operational Metrics Mean Time. Before Failure (MTBF), Mean Time to Repair (MTTR): The gathered pre- and post-implementation data were analyzed using the paired t-tests to ensure the changes were statistically significant and illustrated in **Fig. 9**.

Table 5. *Before and after values for metrics*

Metric	*Before System*	*After System*	*p-value*
MTBF (hours)	145.2	198.7	0.003
MTTR (hours)	6.4	4.8	0.012
Cost per Breakdown ($)	1,470	895	0.005
Technician Utilization (%)	68.2	84.6	0.009

Key Findings:

- All the parameters mentioned in **(Table 5)** were found to have a statistically significant improvement ($p < 0.05$).
- This means that a higher MTBF is an indication of reduced equipment failures.
- Fewer minutes to total time to repair and less cost underscore more effective and timely responses.

Practical interpretation, limitations and effectiveness: The identification of equipment in need of repair or replacement with an analysis of when failures are expected to occur. The findings reveal that it is possible to identify failure signals in advance using machine learning. Applying prescriptive logic further adds value to the generic predictions to ensure they are relevant in the required context.

System strengths:

- Improved decision speed and accuracy.
- Better allocation of parts, technicians, and downtime windows.
- Reduced over-maintenance from calendar-based strategies.

Observations:

- **MTBF Improvement:** The use of predictive maintenance also helped in improving the average time between failures. Before the implementation of the MTBF program, the MTBF was 145.2 hours, while after the implementation, it was 198.7 hours, thus implying that the reliability of the equipment had improved.
- **Faster Failure Repair:** In maintenance, failures were handled and resolved in a shorter period; MTTR reduced from 6.4 hours to 4.8 hours. This is important in avoiding much disruption of production schedules and in the overall cutting of operational costs.
- **Cost Savings:** Other expenses that were also affected include maintenance costs, which recorded a reduction in costs. Some preventive aspects include the reduction of cost per breakdown from $ 1470 to $ 89,5, meaning that flushing revenues may be gained through changing to these sophisticated maintenance strategies. This has been made possible through a reduction in unplanned downtime and optimization of resource use in the organization.
- **Increased Technician Productivity:** The productivity of the technicians was improved through utilization that rose from 68.2% to 84.6%. This implies that technicians were able to perform more preventive or planned maintenance than emergency or corrective maintenance.

Implementation Challenges: On the same note, deployment brought the following challenges to the table:

- Data Issues: The format and content of sensor logs varied a great deal, and this affected the creation of the model.
- User Trust: Some technicians were initially reluctant to use it and needed to be trained and convinced.
- New failure types appeared that were not presented in the training set.

Recommended Solutions:

- Feedback controls that include training models on recent data are also employed.
- To enhance the confidence of the technicians, it is recommended to adopt explainable AI models.
- Include redundancy and override controls for special or unique circumstances in the Reliability Block Diagram (RBD).

IV. Discussion

This research evidence indicates that the effectiveness and applications of both predictive and prescriptive maintenance systems should not be underestimated as they hold the key to increasing efficiency, decreasing downtime, and decreasing general maintenance costs. The utilization of data and computer learning techniques helps organizations move from a reactive maintenance approach to a more efficient predictive routine, thus improving the operations of the organization.

The results showed that there were positive changes in the major areas of maintenance, such as MTBF, MTTR, and cost of maintenance. The application of predictive maintenance made it easier to identify probabilities of equipment failures and make the right interventions at the right time. This proactive approach helped to decrease the rate of emergent failures and, therefore, enhance the reliability of the equipment.

Prescriptive maintenance, however, was a step further than just predictive since it offered solutions. It provided the best recommendations for actions based on the failures that are expected to occur and enhanced the decision-making process and repair activities. By predicting and prescribing the maintenance actions, it was possible to achieve significant decreases in both downtime and repair time, thus enhancing the operation's efficiency.

Recommendations: There is a need to increase the application of predictive and prescriptive maintenance solutions across organizations since they enhance the efficiency of critical machinery and equipment in production.

- **Sustaining the Process:** For the benefits to be fully attained, the performance indicators should be constantly checked and the models refined. The maintenance strategies should, therefore, be refined as more data is obtained to make them more accurate and effective.
- **Invest in Training:** For the effective and efficient implementation of the maintenance strategies, the maintenance teams should be trained not only on the technical aspect of the systems but also on how to understand the results of the prescriptive and predictive maintenance tools.

These maintenance strategies are effective when adopted in combination as a way of improving efficiency, cutting costs, and improving operational performance. As the industries advance, the use of other intelligent technologies, such as predictive and prescriptive maintenance, will be vital for the success of the companies.

Table 6. *Average performance metrics across datasets in existing research*

Metric	***Estimated Average Value***	***Notes***
Accuracy	~88.8%	Averaged from SECOM RF (~66.5%), NASA RF (~98.1%), CM1 SVM (~97.7%)
Precision	~0.71	Primarily from SECOM RF and SECOM GB; MIMII and NASA report sparsely
Recall	~0.80	Gradient Boosting (SECOM) and RF (NASA) emphasize defect sensitivity
F1 score	~0.79	High for NASA CM1 RF (97.25%), moderate for SECOM (~0.69), inferred for MIMII

A review of existing literature illustrated **in (Table 6)** revealed multiple studies focusing on predictive maintenance using similar datasets; however, there appears to be a notable gap in research related to prescriptive maintenance. This gap served as the impetus for the present study. One relevant document identified on the NASA website—Teubert et al. [19], *An Analysis of Barriers Preventing the Widespread Adoption of Predictive and Prescriptive Maintenance in Aviation*—highlights the limited implementation of prescriptive maintenance within the aviation industry.

The predictive models examined in this study, developed using selected datasets, exhibit improved statistical performance relative to the average results reported in earlier studies. Nevertheless, direct comparisons are inherently limited due to methodological and evaluative differences between this study and previous work.

V. PRACTICAL IMPLEMENTATION STEPS

Step 1: Historical Data Collection

- Collect breakdown and maintenance logs from the history of past work orders.
- This step is the biggest challenge in most industries, as the data should be reliable to train the models on it and it should be in a format which has sufficient details to be consumed by the models.

Step 2: Feature Engineering & Failure Pattern Extraction

- With the help of maintenance and reliability experts identify the key data elements which should be used in prediction.
- Remove the faulty entries and fill up the blanks with average or any other method agreed with the experts.
- Apply statistical analysis or ML feature selection to highlight failure precursors.

Step 3: Predictive Model Deployment

- Train Random Forest model using historical patterns.
- Evaluate performance using metrics such as accuracy, precision, recall, and F1 score.

Step 4: Real-Time Monitoring Integration

- Ingest the live data from sensors to build the time series data and use in the prediction model.
- Trigger early warnings when predicted failure probabilities exceed defined rules.

Step 5: Prescriptive Logic Engine

- Map predictive outputs to suggested actions depending on the predefined conditions.

Step 6: Maintenance Decision Execution

- Based on recommendations plan the work orders with prescribed activities.

- Technicians execute the planned work generated from the predictive models containing prescribed activities.

Step 7: Feedback & Continuous Learning

- Technicians document post-maintenance results preferably using pre-defined codes and additional details in the text for model retraining.
- Based on feedback, analyze false alarms and missed failures to refine rules and model features. The feedback from technicians is critical in this step to improve the models and increase the accuracy of the predictions and prescriptions.

VI. Conclusion

The findings highlight MTBF improvement, more efficient failure repair, increased cost saving and technician productivity shows that the use of predictive and prescriptive maintenance is very beneficial for asset heavy industries that use a lot of machinery and equipment. It involves methods that not only save expenditure but also give effective operation and reduce the dependence on worker's reliability.

The use of predictive and prescriptive maintenance systems also has strategic benefits for any business that wishes to remain relevant in the current world that is characterized by the use of data. They enable organizations to achieve the highest possible life-cycle efficiency of the assets, to minimize the risk of failure, and to maintain the highest levels of performance at all organizational levels.

AUTHOR CONTRIBUTIONS

A. Saxena: Conceptualization, Experiments, Theoretical analysis, Evaluation, Writing, Editing

Disclosure Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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