Machine Learning and Optimization for Predictive Maintenance based on Predicting Failure in the Next Five Days

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Abstract: This study proposes a framework to predict machine failures using sensor data and optimize predictive/corrective maintenance schedule. Using historical data, machine learning (ML) models are trained to predict the failure probabilities for the next five days. Multiple algorithms, including feature extraction techniques, selections, and ML models (both regression and classification based) are compared. The machine learning models' output is fed to an optimization model to propose an optimized maintenance policy, and we demonstrate how prediction models can help increase system reliability at lower costs.

1 INTRODUCTION

With the rise of digitization, Artificial Intelligence (AI) implementation in companies can help them become more efficient and competitive. One application of AI is through the integration of machine learning and maintenance. Companies rely on three types of maintenance for their machines (Carvalho et al., 2019; Lee and Scott, 2009):

1. Run to failure, also called corrective maintenance, is when maintenance is conducted only when the machine fails. This causes a longer downtime period and has a high cost because it causes lags in the processes and the tasks of the machines.
2. Preventive maintenance, also called time-based maintenance and scheduled maintenance, is when maintenance follows a schedule periodically. Although failures are prevented, maintenance is done before the machine fails and it may be unnecessary.
3. Predictive maintenance uses predictive tools to estimate when maintenance is necessary. It monitors the machine health continuously over time and allows for early detection of failures based on historic data.

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The significance of predictive maintenance has increased in the last decades with advances in sensoring and Internet of Things (IoT) technologies. The main advantage of the predictive maintenance that it can minimize the downtime and related costs, can help to increase the lifespan of the equipment.

There are multiple techniques that can facilitate predictive maintenance. One technique is relying on historical data by analyzing it using machine learning (ML) methods and tools. ML methods nowadays are faster when compared to ordinary statistical survival analysis, due to the greater availability of computing power for sensors and failure data collected in the last years.

This study applies feature engineering techniques and machine learning models on sensor data to predict the failure probabilities up to five days in advance. Different machine learning models from the literature are compared to find the highest accuracy. The obtained failure probabilities are used further in the proposed optimization model to create the optimum maintenance schedule. In this way, the machine learning methods, big data, and optimization models are put together to create an efficient predictive maintenance policy. To the best of the authors' knowledge, a simplified optimization model that uses the failure probabilities of multiple machines from machine learning algorithms has not been formulated.

The remainder of the paper is organized as follows. Section 2 includes a literature review on machine learning methods for predictive maintenance

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and mathematical models used. Section 3 introduces a methodology to define the libraries and models utilized in this paper. Section 4 presents the results, and the conclusion demonstrating the findings is given in Section 5.

2 MACHINE LEARNING IN PREDICTIVE MAINTENANCE

Researchers categorize machine learning models into three types (Cai et al., 2018): supervised learning, unsupervised learning, and reinforcement learning. Supervised learning includes both regression and classification problems. On the other hand, unsupervised learning uses clustering and association to find the inherent groupings in the data and detect rules to describe it. This part of the review covers the different methods to use machine learning for predictive maintenance in literature. The utilization of ML in predictive maintenance can help in using different strategies. These include regression models to predict the remaining useful life (RUL) and classification models to predict failure in a given time window.

Regression is used when problems are needed to predict results based on continuous input and continuous output. Hence, various studies use it to predict the RUL of machines. One of the studies is a comparative analysis for regression is done for predicting the RUL (Yurek and Birant, 2019). Two methods are used to calculate the RUL from The Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset before running the regression models. The first approach uses the difference between the current time of the machine and the fault time is calculated. In the second approach, the running time is calculated which is the maximum value of RUL for each failure. The author used Azure Learning Machine to apply multiple feature selection methods and different machine learning algorithms. The study included 72 different models with different feature selection methods and machine learning models combinations. The author compared the results and concluded that the Decision Forest Regression achieves the least prediction error.

Classification is used in machine learning to classify faults and predict their probability. One study uses the Azure Machine Learning tool to train a Multiclass Decision Forest model (Paolanti et al., 2018). The authors achieved an accuracy of 95% on data from a cutting machine. The proposed method estimated parameters ahead of time. The predicted value is at time $t + dt$ where t is the time of the readings and dt is the time ahead. Another research also uses this method for vibration signals (Amihai et al., 2018). The authors form a supervised learning problem by having features and creating labels. Moreover, the values are of readings are at certain points in time and the labels are ahead of time. Further, the authors used Python and R for data processing, analysis, and modeling. Additionally, another research also uses Python to classify faults in wind turbines using machine learning models (Hsu et al., 2020). With 92.7% accuracy for the decision tree model and 91.9% for the random forest model.The authors test it using K-fold cross-validation to verify the model and decrease the probability of false alarms. Moreover, Kusiak and Verma also used condition-based monitoring tools to identify potential faults (Kusiak and Verma, 2012). Additionally, another study performs a comparative analysis of the classification of four different classes. It uses five different machine learning algorithms. (Neural Network, Support Vector Machine, Random Forest, Boosting Tree, and General Chi-square Automatic Interaction Detector). The data used is from large wind farms with 17 wind turbines. It proved that Random forest algorithm model produces the best accuracy of 98%. Another study also generates models using the Random forest approach with number of trees = 40 and maximum depth = 25 (Canizo et al., 2017). The values were chosen based on the trial and error of several predictive models and methods to find the best values. The study uses Big Data and processes it to generate predictive models. The Pearson correlation for feature selection is used and the accuracy produced reached 82.04%. Using Python to process the data and build a model is feasible. When it comes to predicting faults and classifying them, the decision tree models produced the highest accuracy in the studies reviewed.

Although the majority of the aforementioned papers concluded that the decision tree algorithm provides high accuracy, other feature engineering methods can be used to boost accuracy. One is a dimension reduction method done for classification (Aremu et al., 2020). The authors used the Machine Learning Dimension Reduction framework (MLDR-framework) and produced higher accuracy. This explains how researchers can use feature selection methods to increase the accuracy of results. Another study uses AutoRegressive Integrated Moving Average (ARIMA) to predict failures and classify faults (Kanawaday and Sane, 2018). The ARIMA model was used to predict future data points. They use data collected from a slitting machine. The four models used are Naïve Bayes, Support Vector Machine, CART, and Deep Neural Network. Accuracies were 96%, 95%, 94%, and 98% respectively. Moreover, other studies have implemented unsupervised learning algorithms. The authors in (Amruthnath and Gupta, 2018) use unsupervised learning on exhaust fan vibration data for predictive maintenance and propose a method using R programming. They conclude that clustering algorithms are best for fault detection under different levels. Overall, when studies use the right techniques, unsupervised models may perform better than decision trees. However, due to its simplicity, only supervised models are studied in this research.

Condition-based monitoring that depends on optimization models is widely available in the literature. Literature reviews usually focus on single components (Alaswad and Xiang, 2017; Sakib and Wuest, 2018). Due to the limitations of complexity, the study of multiple component systems in predictive maintenance in literature is not widely covered. The dependence of the components and their level makes it harder to construct an effective model. For illustration, a single component mathematical optimization model is studied for condition-based maintenance (Tian et al., 2012). For single-component models, as the reliability increases, the cost increases. Reliability is the probability of preventive maintenance. Hence, the objective function is to minimize the cost for optimum maintenance. Moreover, another research studies multiple components into consideration (Einabadi et al., 2019). The indices were the number of parts, periods, and machines. Different costs were considered such as the cost of repair, renewing, and purchasing. The decision variables include timings of when a component must be replaced and the time of maintenance. These additional features helped in this research to put together an optimal maintenance schedule.

Another type of research refers to a threshold to compare the probability of failure (Nichenametla et al., 2017). Once a component exceeds the threshold, maintenance is required. The higher the probability of failure of the machine, the higher the priority of inspection. The authors establish threshold targets by probability plots and reliability comparisons. Furthermore, another study presents a unique model called Preventive Maintenance Scheduling Problem with Interval Costs (PMSPIC) with an objective to minimize maintenance costs. (Bangalore and Patriksson, 2018). It takes into consideration both age-based and cost-based failure rates. A different cost model takes into consideration repair costs, downtime cost, and set-up costs performed an opportunistic PdM strategy (Hu et al., 2012). However, the maintenance strategy is to put the machines in groups. The strategy suggests that maintenance may be executed in groups and it decreases costs as low as possible. Additionally, another study also groups the machines (Vu et al., 2020). The authors in the research use Genetic Algorithm with Memory (GAM) to group the machines into groups in certain time slots to decrease the costs. Figures 1 and 2 show the original maintenance plan and the modified one. Since maintenance is implemented groups in the same time period, it produces a lower cost. In conclusion, the method of grouping machines to perform maintenance is an efficient method to decrease the cost as much as possible.

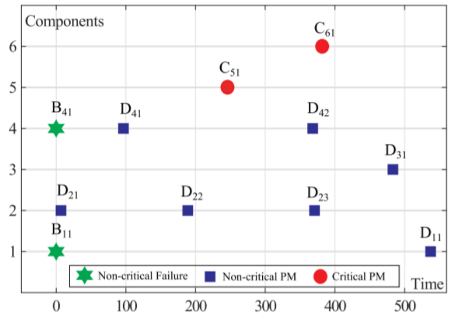

Figure 1: Original schedule before grouping components.

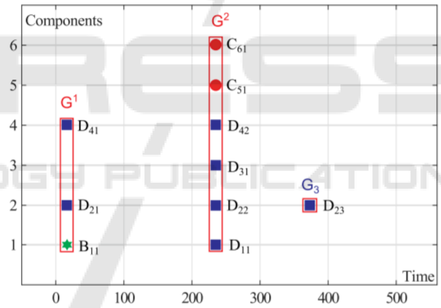

Figure 2: Schedule after grouping components.

3 PROPOSED METHODOLOGY

The methodology section focuses on two parts. First, the machine learning phase which consists of the following steps:

1. Historical data selection: Selection of sufficient historical data to process.
2. Data preprocessing: The data is modified through feature engineering to be suitable to be fed into the model.
3. Model selection: A suitable model is chosen to based on the given dataset and the application.
4. Model training and model validation: The data is fed into the machine learning model and validated.

The second phase consists of the mathematical model to minimize the cost of the overall maintenance of the machines. The full model diagram is shown in Figure 3. Sensor data is the input to the model and the final output is a decision of the number of machines to be maintained.

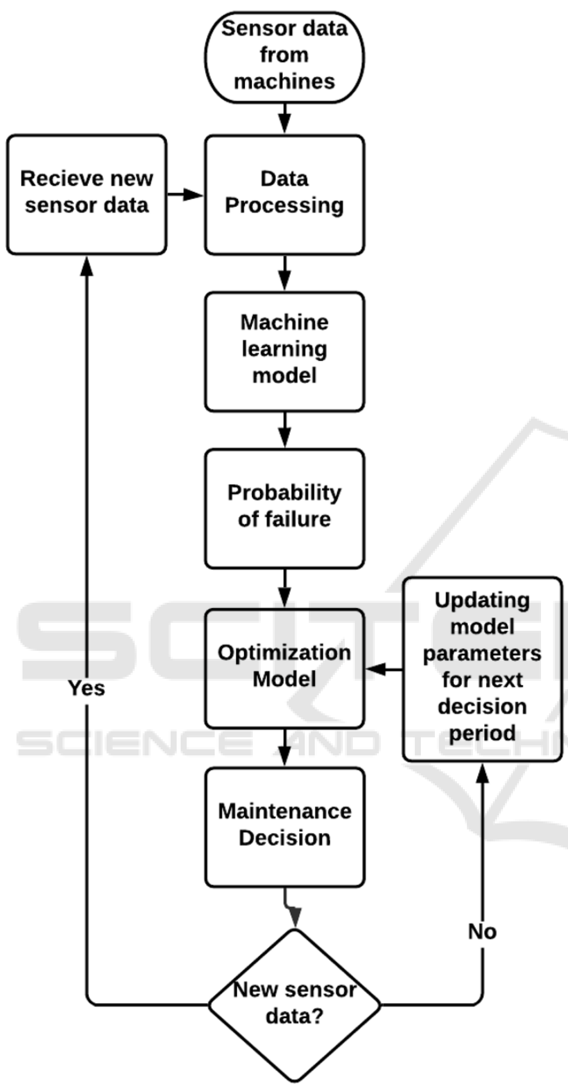

Figure 3: Proposed model diagram.

3.1 Proposed Machine Learning Model

3.1.1 Data Preprocessing - Format and Label

The data used has to be relevant, sufficient, and of high quality. Therefore, understanding the data is crucial. During the data preprocessing step, feature engineering was used to frame the problem appropriately. Feature extraction is a part of feature engineering and is used to generate features from the existing data by changing and transforming it. Moreover, feature selection is useful to eliminate unnecessary data from the dataset (Cai et al., 2018). It reduces the dimensions which can give us better models for machine learning. In supervised learning, this is usually done manually.

The dataset in this study is obtained from the datasets used by Fidan Boylu Uz in "Predictive Maintenance Modelling Guide" (Uz, 2016). It contains sensor readings from 100 machines. Originally, five different datasets are given and a sample of each one is shown in Table 1. Moreover, these are merged into one big dataset and the columns are considered the features. However, feature engineering plays a role here and other features are extracted from the original dataset. The important additional features are shown in Table 2. The final features are then used to feed the machine learning model and predict failures in advance.

From the features, it is important to have sufficient data to answer the question the machine learning model output is expected to answer. The data is measured in time stamps. Hence, some of the timestamps may not have recorded data. Therefore, handling the missing data is important. The average of each over 24 hours is taken, this feature engineering step eliminates the problem of having missing data. Moreover, decreases the data points from 876,100 to 36,600 readings eases data handling. The last feature in Table 2 represents the labels of the dataset. In every model, a different column is targeted as the label feature. Parameter dt ranges from 1 to 5 and each number represents the number of look-ahead days to be predicted.

3.1.2 Machine Learning Algorithms

In this study, three machine learning algorithms are used to predict the failures, namely, Logistic Regression, Random Forest and Gradient Boosting Classifier. The Scikit-learn library was used for predictive analysis and machine learning models. The machine learning model is used to predict the failure days in advance. Depending on dt, the number of days in advance, the label is predicted. Different machine learning models are trained every time to predict the different days. The label is either a 0 or 1; 1 is a prediction that failure will happen after dt days. The probability of every class can also be extracted. Hence, we achieve the probability that a failure will occur.

The data is then split into testing and training. The dataset consists of data for one whole year. The first three quarters of the year are used to train the model. The last quarter was used for testing. The lowest testing accuracy of the two classes is recorded.

Table 1: The given datasets.

Dataset	Given Columns/Features		
Telemetry	datetime	machineID	volt
	1/1/2015 6:00	1	176.21
	vibration	pressure	rotate
	45.087	113.078	418.50

Errors	datetime	machineID	error ID
	1/3/2015 7:00	1	error1

Machines	machineID	model	age
	1	model3	18

Maint	datetime	machineID	comp
	6/1/2014 6:00	1	comp2

Failures	datetime	machineID	failure
	1/5/2015 6:00	1	comp

3.2 Optimization Model

The proposed mathematical model reduces maintenance costs. Costs are split into different parts. Including costs of labor, repairing, renewing, or replacing. The costs depend on what state the machine is at. At each state $s = 0, \ldots, S$, the probability of failure decreases until it reaches state 0 which is the failure mode. At failure mode, it is assumed that the machine would need replacement and the cost would be highest.

Indices:

t – Days Index ($t = 1, \ldots, T$).

s – State Index ($s = 0, \ldots, S$).

Parameters:

M – Minimum number of working machines in day t.

C_s – Cost of fixed maintenance for one machine from state s.

$P_{ss'}$ – Probability of moving to state s to s'.

Decision variables:

X_{st} – Number of machines maintained at state s in day t.

Y_{st} – Number of machines in state s at day t.

Table 2: Additional features added to the dataset.

Feature	Explanation
Volt_ 24hr mean	The Average of the voltage over the past 24 hours.
Volt_ 24hr std	The standard deviation of the voltage over the past 24 hours.
Volt Moving Av	The average voltage within a time window. The time window is two days used for this study.
Volt Moving Std	The average voltage within a time window. The time window is two days used for this study.
Volt Expanding Av	The average of all voltage readings since last maintained.
Volt Expanding Std	The standard deviation of all voltage readings since last maintained.
Total Errors	The total number of errors in the past 24 hours.
Last failure	Number of days since the last failure occurred.
Last maintenance	Number of days since the last maintenance occurred.
Failure $(T+dt)$	Binary 1= Failure 0= No failure dt is time that needs to predicted ahead of time.

Optimization Model formulation:

$$\min \sum_{t=1}^{T} \sum_{s=1}^{S} X_{st} C_s \tag{1}$$

$$\text{s.t. } Y_{st} = (Y_{st-1} - X_{st-1}) \left(1 - \sum_{s'=0}^{s-1} P_{ss'}\right) + \sum_{s'=s+1}^{S} (Y_{s't-1} - X_{s't-1}) P_{s's}, \quad \forall s < S \tag{2}$$

$$Y_{St} = Y_{St-1} \left(1 - \sum_{s'=0}^{S-1} P_{Ss'}\right) + \sum_{s'=0}^{S-1} X_{s'\mathrm{t}-1} \tag{3}$$

$$\sum_{s=1}^{S} Y_{st} \geq M \tag{4}$$

$$X_{st} < Y_{st} \tag{5}$$

$$X_{st}, Y_{st} \geq 0 \tag{6}$$

In this formulation, objective (1) is set to minimize the cost of maintenance, where C_s is the cost of repairing machines in state s to the fully operational state.

Constraints (5) ensure that the number of machines repaired in a certain state must be less than the total number of machines in that state. Constraints (6) ensure that the number of machines remaining in a certain state (Y_{st}) or being repaired from a certain state (X_{st}) must be non-negative. Constraints (2) ensure that the total number of machines at each state at a certain point in time considers the previously repaired machines and the probabilities of failure. Constraints (3) are similar to constraints (2). However, they only apply to the final state and include all the previously repaired machines. Constraints (4) ensure that the number of machines working at a certain point in time is greater or equal to M. M is the minimum number of operating machines required.

The number of machines that should be maintained from different states on the next t number of days is decided. This is the predictive maintenance decision. We can consider the costs to be corrective maintenance if we wait till the machine reaches failure mode and then repair or replace it. Hence, comparing both approaches is the methodology adopted in this research.

4 CASE STUDY

4.1 Input Data

In this section of the results, the input data to the machine learning model and the optimization model are defined. First, the data used to train and test the machine learning model is the same dataset analyzed in Section 3. Then, the obtained predicted probabilities are extracted and used in the optimization model.

In this study case, there are initially 100 machines at the fully operational state and are then classified into *three* states:

1. Failure state
2. Suspicious Failure state
3. Fully Operational state

At each state, the average of all the machines' probabilities is calculated. The Suspicious Failure state probability to the Failure state is extracted from machines with a probability of failure greater than 80%. The Fully Operational state to the Suspicious Failure state probability is resulted from machines with a probability of failure between 20% and 80%. The Fully Operational state to the Failure state probability is assumed to be 10%, because of the uncertainty in the model and that there is always a chance of sudden failure.

Furthermore, the distribution of the maintenance costs in this study case shown in Figure 4 is based on justifiable assumptions. The costs of repair at Fully Operational state and Suspicious Failure state are assumed to be 1 unit and 3 units respectively. As mentioned in Section 3, we expect the Failure state to cost more than other states an this why it assumed to cost 6 units per machine. The cost of repair at a fully operational state and is considered low because it includes inspection costs.

Additionally, we assume that M, the minimum number of machines operating, is 80. The maintenance decision of the next $five$ days is made.

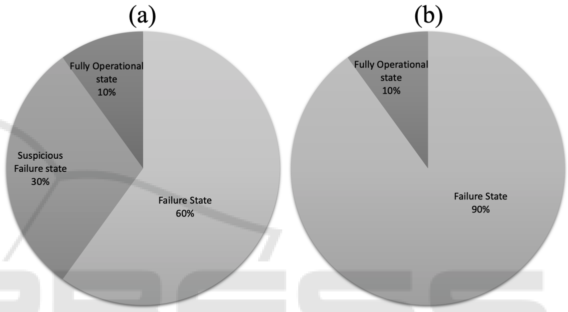

Figure 4: (a) Predictive maintenance cost distribution. (b) Corrective maintenance cost distribution.

4.2 Results

In this section, the results of both the machine learning model and the optimization model are illustrated. Three machine learning models, Logistic Regression, Random Forest Classifier, and Gradient Boosting Classifier, are used to calculate the probability of failure. Since the output is classified to be either 0 or 1, the class with the lowest accuracy is recorded. The accuracy also corresponds to the recall score and the lowest recall score is noted. Figure 5 shows the results of the three models in predicting failure in the next five days. Gradient Boosting classifier appears to produce the best result in all five days. The probability of failure of each machine is predicted from the gradient boosting classifier. Using the assumptions mentioned in Section 4.1, the machines are split into three different states based on the probability values. At each state, the average of the probabilities is calculated and the results are listed below.

- Fully Operational state to the Suspicious Failure = 0.3
- Suspicious Failure state probability to the Failure

state = 0.9

The probabilities of failure are then fed into the optimization model presented in 3.2 along with the inputs discussed in Section 4.1. A linear program solver is used and the model maintenance policy suggests that within the next 5 days, the total number of machines inspected or repaired at each state is as follows:

1. Failure state – 17 machines.
2. Suspicious Failure state – 87 machines.
3. Fully Operational state – 0 machines.

Given this predictive maintenance approach, the total cost of keeping 80 machines operating is 363 units. However, when using the corrective maintenance approach, the machines are repaired only at Failure state and inspected at the Fully Operational state. Hence, the Suspicious Failure state is not accounted for and all machines in this state are assumed to reach the Failure state. This further justifies Figure 4. According to the predicted probabilities of failure, in total, 104 machines should be maintained. Further, as mentioned in Section 4.1, the corrective costs are 6 units. The addition of all costs outputs the costs of corrective maintenance; $104 \times 6 = 624$ units. In comparison with the 363 units calculated by the proposed maintenance policy, this is close to a 50% increase in cost. The prediction model calculated a lower cost because 87 out of 104 machines could be repaired early and avoid high corrective maintenance costs. Hence, the predictive maintenance model achieves the same goals at lower costs and is solved within a few seconds, on a consumer's laptop. The proposed model can be applied to more than three states and achieve efficient maintenance policies.

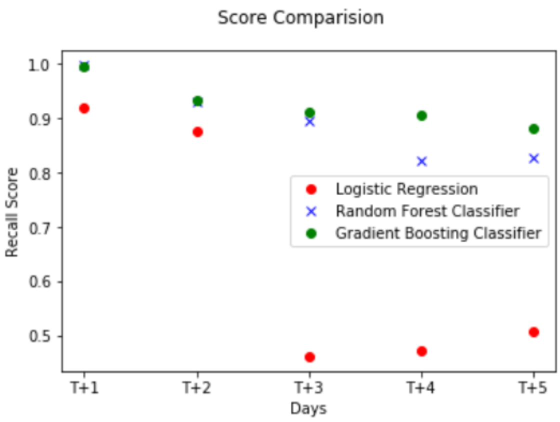

Figure 5: Accuracy comparison between different machine learning models.

5 CONCLUSION

In conclusion, this study develops a framework to reduce maintenance costs using both a machine learning model and an optimization model. Three different machine learning models were compared on the given dataset and the gradient boosting classifier produced the highest prediction accuracy reaching 99% for one day in advance prediction. Moreover, the suggested maintenance policy was applied and compared to a conventional corrective policy. It displayed how having a predictive maintenance policy can increase system reliability and decrease costs.

This study faces two main limitations. First, the dataset is imbalanced. The number of failures is the minority in the dataset. Hence, feature engineering techniques must be used to balance out the dataset before feeding it into the machine learning models. Another limitation in this study was the costs of maintenance. They were given assumed values due to not having sufficient and exact data about the cost of repair at each state.

For the prediction model, future works may include other feature engineering techniques to produce higher accuracy. Big data may also be used along with other regression models to predict the remaining useful life of the machine. Moreover, deep learning can be implemented on the dataset used in this research to avoid feature selection. For the mathematical model, future works may include maintenance decisions per machine rather than taking an average and expand the schedule to suggest maintenance decisions for more days in advance.

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