Damage Detection on Turbomachinery with Machine Learning Algortihms

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Abstract. This study uses machine learning methods to find deterioration in turbomachine parts. In turbomachines, damage control procedures are carried out at specific times. Even though these checks take a while, if there is no damage, the components won't be replaced, and it is not anticipated that they will be rechecked until the following control or an unforeseen incident. For this situation, a machine learning algorithm has been developed and 96% accuracy was obtained for overall components.

Keywords: Turbo Machinery · Machine Learning · Predictive Maintenance

1 Introduction

This study aims to detect prior damage in turbo-machine components via machine learning algorithms. The damage control process in turbomachines is performed at certain hours. Although these checks take a quite long time, if there is no damage, the components will not be replaced, and the components are not expected to be checked again until the next control or an unexpected event occurs. The general factors that cause gas turbine damage are as follows:

- **Erosion:** Some particles that come with air passing through the compressor can degrade and damage surfaces inside the compressor instead of binding onto them. Erosion damage caused by solid particles is a frequently occurring problem that can affect the components of aeroengines. Both stationary and rotating airfoils are susceptible to material loss due to the impact of erosive particles. In some cases, this damage can result in negative effects on the hot-section hardware and overall engine performance [1].
- **Abrasion:** Abrasion is a type of wear caused by the mechanical action of one surface rubbing against another. It can be caused by a variety of factors, including the hardness and roughness of the surfaces involved, the presence of foreign particles, and the sliding speed and contact pressure between the surfaces. Abrasion can result in surface damage, material loss, and changes in surface properties such as roughness and hardness [2].

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– **Corrosion:** Sulfur from the fuel and sodium chloride from the air interact during combustion at high temperatures to form sodium sulfate. Following deposition, the sodium sulfate speeds up oxidation (or sulfidation) attacks on hot-section components [3] [4].
– **Foreign Object Damage:** Objects going into the compressor may cause severe damage to industrial gas turbines, which are far more prevalent than turbines used on aircraft with open inlets [5].
– **Fatigue:** The beginning and growth of cracks in a material as a result of cyclic loading is known as fatigue. Fatigue can be caused by dynamic loads, vibrations, impacts, or thermal loads [6]. Fatigue can be extremely dangerous for turbo machinery used in aviation. A sudden loss of power may lead to undesired results. Thus, fatigue detection is essential.
– **Thermomechanical Fatigue:** Hot-section components of gas turbine engines operate in a hostile environment and are constantly vulnerable to failure by the thermal fatigue damage mechanism because of the different heat capacities of the various materials in the component as well as a non-uniform temperature field on the component. A gas turbine engine's starting and stopping can cause temperature redistribution in the parts, which can lead to thermal fatigue damage [7].
– **Creep:** Components of gas turbines working at high temperatures gradually deform under the influence of applied stress. Such deformation eventually builds up and causes a creep rupture mechanism, which causes fracture. The main factor reducing blade life in base-loaded gas turbines is blade creep degradation. Critical component design assessment for high-temperature applications should take these deformation and damage processes into account, and engineering calculations call for knowledge of creep rupture characteristics for the material the structure is made of [8].

Supervised learning and unsupervised learning are two major categories of machine learning algorithms that have been widely studied and applied in various fields in recent years. Supervised learning is a type of machine learning where the algorithm is trained on a labeled dataset, meaning that each data point is associated with a known target value. The algorithm learns to predict the target value for new, unseen data based on the patterns it identifies in the training data. Some popular supervised learning algorithms include linear regression, decision trees, and neural networks [9].

On the other hand, unsupervised learning is a type of machine learning where the algorithm is trained on an unlabeled dataset, meaning that the data points do not have any associated target values. Instead, the algorithm identifies patterns and structure within the data itself, without any prior knowledge of what the data represents. Common unsupervised learning techniques include clustering, anomaly detection, and dimensionality reduction [10].

Both supervised and unsupervised learning have their own strengths and weaknesses, and the choice of which type of learning to use depends on the specific problem and data at hand. In recent years, there have been numerous advancements and innovations in both supervised and unsupervised learning, leading to exciting new applications in fields such as computer vision, natural language processing, and healthcare [11].

– **Regression:** Regression algorithms are categorized as supervised machine learning. They support the explanation or forecast of a numerical value based on a collection of historical facts [12].
– **Classification:** Another sort of supervised machine learning that predicts or explains a class value in classification algorithms. They can help anticipate whether an online buyer would purchase a good, for example. Buyer or non-buyer, the response is either yes or no. Classification systems, on the other hand, are not limited to only two categories [12].
– **Clustering:** Since the goal of clustering algorithms is to group or cluster data with comparable features, they fall within the topic of unsupervised machine learning. Approaches that use clustering don't need output data to train. Instead, this method uses an algorithm to decide the result. Only visualizations can be used by a data scientist to evaluate the quality of a clustering algorithm's answer [12].
– **Dimensionality Reduction:** This technique is used in to remove the least related information from a data set. Since data sets containing a lot of columns are common, it is imperative to lower the overall amount. There are thousands of pixels in a photograph, but not all of them are crucial to research. Similar to this, dozens of measurements and tests may be performed on each chip during the manufacturing process, many of which offer redundant data. To manage the data set in these situations, dimensionality reduction techniques will be needed [12].
– **Ensemble Methods:** Ensemble approaches combine multiple predictive models (supervised machine learning) to make better forecasts than any one model could. For instance, an ensemble method known as random forest techniques combines many decision trees that have been trained using various data sets. As a result, a Random Forest's forecasts are more accurate than a single Decision Tree's [12].
– **Neural Networks and Deep Learning:** Artificial networks aim to capture non-linear patterns in data by incorporating multi-layered parameters into the model, as opposed to logistic and linear regressions. [12].
– **Transfer Learning:** Transfer learning is a method where parts of a pre-trained neural network can be reused and adapted for a new but similar task. Specifically, some of the trained layers from the previous neural network, which was trained on a particular task, can be transferred and combined with a few new layers that are trained on the data from the new task. [12].
– **Reinforcement Learning:** Reinforcement learning is an approach that enables an algorithm to learn from previous experiences in a general sense. By observing actions and using a trial-and-error method in a controlled environment, reinforcement learning can optimize a cumulative reward. [12].
– **Natural Language Processing:** This is a frequently used methodology for preparing text for machine learning. The most widely used text processing package is NLTK (Natural Language ToolKit) [12].

– **Word Embeddings:** TTF-IDF is a numerical representation of text documents that considers only the frequency and weighted frequencies of words. Word embeddings, on the other hand, capture a word's context within a document, enabling us to perform arithmetic with words by measuring the similarity of words based on context. Word2Vec utilizes a neural network to convert words in a corpus into numerical vectors, which can then be employed to identify synonyms, conduct word arithmetic, and represent text documents (by averaging all the word vectors in a document) [12].

Since predictive maintenance with machine learning studies has not been done before, the literature research is mostly focused on the use of machine learning algorithms in mechanical engineering, especially in the energy sector.

Regan et al. combined acoustic with machine learning algorithms, and they detected wind turbine blade damage. In the study, Regan et al. used supervised machine learning to accomplish 98% accuracy [13]. Ghalandari et al. optimized the first row of the compressor blade with an artificial neural network. It has been seen for the aerodynamical view, mass flow increased by 4% and for the structural view, optimized blades met the reduced frequency criteria [14].

In the study "Adaptive Detection and Prediction of Performance Degradation in Off-shore Turbomachinery", Zagorowska et al. tried to detect of degradation in turbomachinery. To accomplish that Zagorowska et al. took the data of weather every day for 2 years and trained and tested the algorithm which showed that it is possible to combine the existing approaches in degradation modeling to improve the accuracy of the prediction, thus making the algorithm useful in industrial performance-based application [15].

In a study Gascon et al. identified the machine learning technique that best estimates the remaining useful life of boiler components using plant operations. The best strategy to anticipate the decline in the life span of the plant with over 90% certainty, according to the authors' testing of five different machine learning algorithms [16].

Chao et al. showed that the capacity to estimate the remaining usufel lifetime (RUL) of its components, is a crucial enabler of intelligent maintenance systems. Datasets with run-to-failure trajectories are required for the creation of data-driven prognostic models. Chao et al. create a new dataset of run-to-failure trajectories for a fleet of aircraft engines under real-world flight conditions to aid the development of prognostics algorithms. The dataset was created using the NASA-developed Commercial Modular Aero-Propulsion System Simulation (CMAPSS) model. The damage propagation model employed in this dataset expands on earlier work's modeling method and adds two new levels of accuracy [17].

As above mentioned, there are no studies on this subject. In this study, various methods were tried to create a database due to the lack of databases or not being shared, and these methods were mentioned in the methodology section. For a quick solution, the classification method mentioned above is used.

2 Methodology

In order to apply Machine Learning technique, the necessary dataset has been obtained from NASA The Prognostics Data Repository [18] which is studied at study of Chao et al. [17]. Figure 1 shows schematic illustration of the engine along with the CMAPSS model's assigned station numbers.

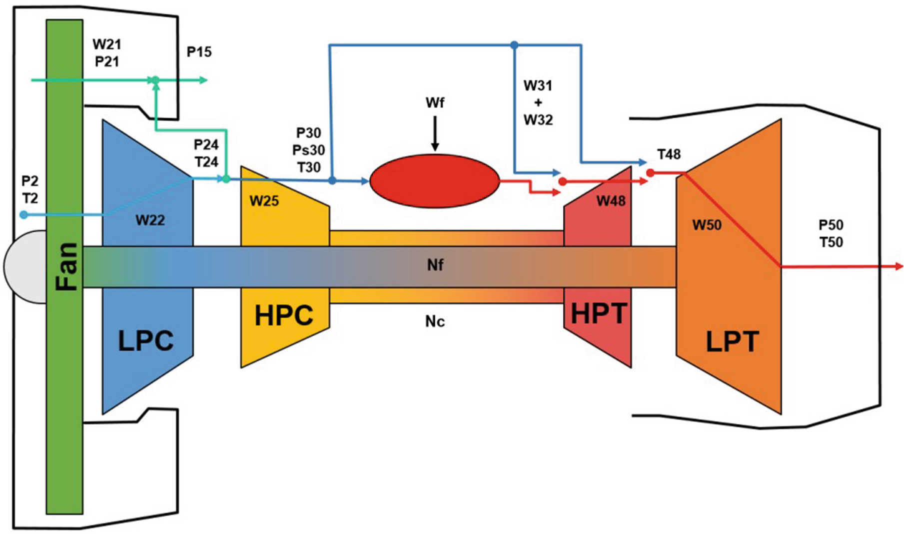

Fig. 1. Schematic representation of the CMAPSS model [17]

The names, descriptions, and units of each input variable in the dataset are can be found in study of Chao et al. [17]. In the CMAPSS model, the variable symbol corresponds to the internal variable name. The model documentation is used to generate the descriptions and units [19].

The output of the data is reaming useful life (RUL). For flight classes 8 and 9 RUL table has been shown in Fig. 2 below. For the study, all flight data has been merged. Due to the enormous number of data (sixty-nine million columns), an algorithm was created for data reduction. This algorithm was used to generate the dataset from 99 rows and 104 columns. The flow diagram of the algorithm is shown in Fig. 3.

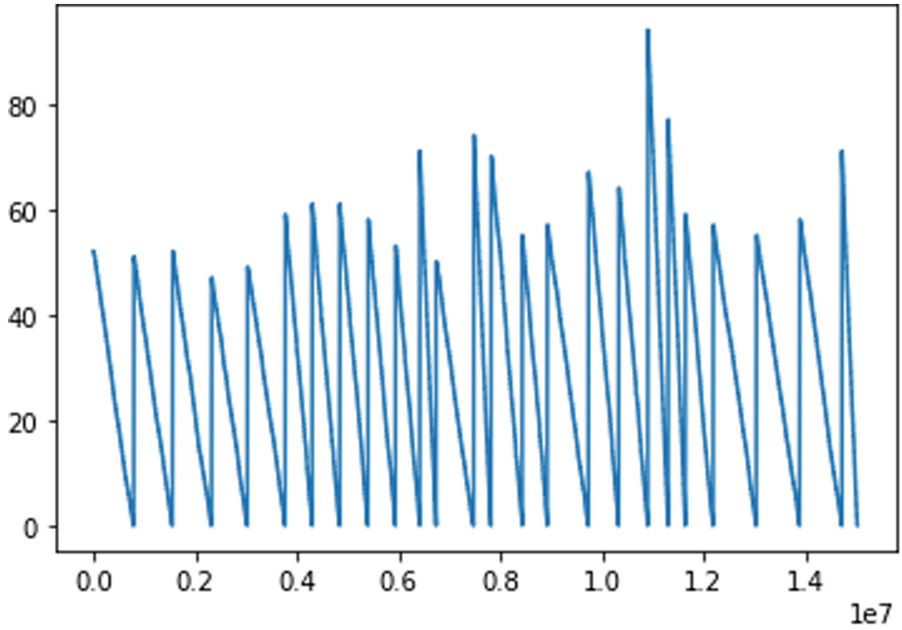

Fig. 2. RUL for Flight Cases 8 and 9. [19]

Due to the lack of maintenance data, failure output data is created with the reduced data. Table 4. shows which damage mechanism affects the sensor or measurement values as follows (Table 1):

Table 1. Sensors that Affect Damage Mechanism

	RPM	Temp	Pre	Flow	phi	Fatigue
Fatigue	+	+	–	–	–	–
Creep	–	+	–	–	–	+
Erosion	–	+	+	+	–	–
Abrasion	–	–	–	+	–	–
Thermomechanical Fatigue	–	+	+	–	+	–
Corrosion	–	+	–	–	+	+

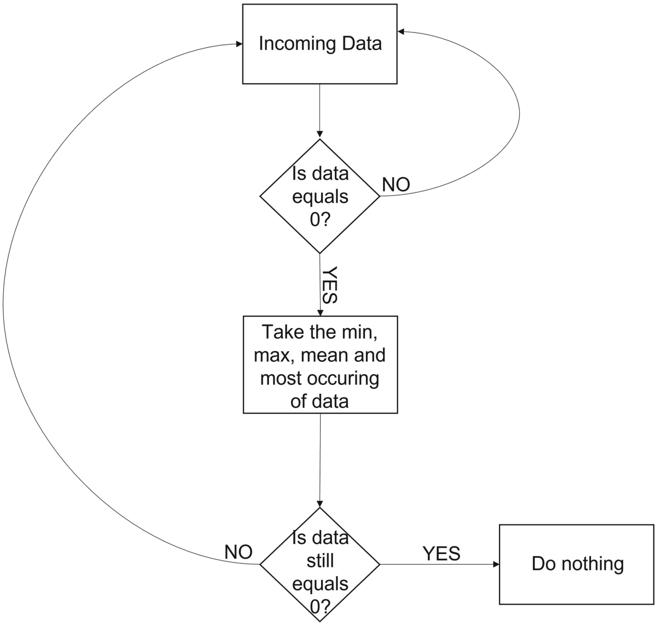

Fig. 3. Flow Chart for Data Reduction Algorithm.

These relations have been gathered from the study of "Taxonomy of Gas Turbine Blade Defects" [20] and other literature surveys. It can be seen in Table 2 that damage mechanisms occurred in components. Due to the lack of output data (which is all zero and because of that A.I. will not learn from it) LPT damage mechanism only consists of fatigue and creep.

Table 2. Damage Types for Components

	Fatigue	Creep	Erosion	Abrasion	Thermomechanical Fatigue	Corrosion
LPC	+	+	+	+	–	–
HPC	+	+	+	+	–	–
Burner	+	+	+	–	+	+
HPT	+	+	+	–	+	+
LPT	+	+	–	–	–	–

According to the relationships in the data set, if the output is one, there is damage, if the output is zero then there is no damage. The classification method was chosen for Machine Learning algorithms because of the probability of damage. All classification techniques have been used and the accuracy scores compared.

3 Results

After data processing is done, the classification technique is chosen for the Machine Learning Algorithm due to quick solution and computer power. Each damage of each component was put into the algorithm separately. 80% of the dataset was reserved for training and the remaining 20% was for testing.

For classification tasks, the mean accuracy can be calculated as the average of the accuracy scores for each class. The formula is:

$$mean\ accuracy = (accuracy\ of\ class\ 1 + ... + accuracy\ of\ class\ n)/n \quad (1)$$

Here, n is the number of classes in the classification problem [21]. Accuracy scores are shown below:

Table 3. Accuracies for LPC

	Fatigue	Erosion	Creep	Abrasion	Mean
LR	.85	.95	1	.95	.9375
KNN	.85	1	1	1	.9625
SVM	.9	.95	1	1	.9625
Kernel SVM	.8	.95	1	1	.9375
Naive Bayes	.8	.75	1	1	.8875
Decision Tree	.8	.9	1	.9	.9
Random Forest	.85	.95	1	1	.95

According to Table 3, SVM performs better than the other models in terms of accuracy, while Naïve Bayes performs worse. This difference can be attributed to the fact that Naïve Bayes assumes that each feature is independent of the others, whereas SVM takes into account how the features interact with one another. Although the results showed that all the features had a value of 1, indicating the possibility of overfitting, the R2 test was repeated to confirm that overfitting was not a problem.

Table 4. Accuracies for HPC

	Fatigue	Erosion	Creep	Abrasion	Mean
LR	.75	1	1	.85	.9
KNN	.95	.95	1	.95	.9625
SVM	.85	1	.95	.95	.9375
Kernel SVM	.8	.9	1	.95	.9125
Naive Bayes	.8	.85	.8	.85	.825
Decision Tree	.95	.9	1	1	.9625
Random Forest	.8	.9	1	.95	.9125

Table 4 shows that KNN has the highest average score, while Naïve Bayes has the lowest. The primary reason for this difference is that KNN is a discriminative classifier, whereas Naïve Bayes is a generative classifier.

Table 5. Accuracies for Burner

	Thermal Fatigue	Fatigue	Erosion	Creep	Corrosion	Mean
LR	.9	.95	.9	1	1	.95
KNN	.9	1	.9	1	.95	.95
SVM	.95	.95	.95	1	1	.97
Kernel SVM	.9	.95	.9	1	1	.95
Naive Bayes	.85	.9	.85	1	1	.92
Decision Tree	.9	.95	.9	1	1	.95
Random Forest	.9	.9	.9	1	1	.94

Table 5 indicates that SVM has the highest average score, while Naïve Bayes has the lowest score, once again. As previously explained, this is due to the different approaches used by these techniques in addressing the problem. While one treats each data point independently, the other considers them as related. It's worth noting that even though the creep scores are all 1, the R2 test has been conducted to confirm that overfitting is not a concern.

Table 6. Accuracies for HPT

	Thermal Fatigue	Fatigue	Erosion	Creep	Corrosion	Mean
LR	.8	1	.95	.9	.8	.89
KNN	.85	1	.95	1	.8	.92
SVM	.85	1	.95	.95	.95	.94
Kernel SVM	.8	1	.95	1	.8	.91
Naive Bayes	.6	1	.95	.75	.75	.81
Decision Tree	.9	1	1	1	.95	.97
Random Forest	.85	1	1	1	.75	.92

Table 6 shows that SVM has the highest average score, while Naïve Bayes has the lowest score, as previously mentioned. This difference can be attributed to the different approaches used by these techniques. While SVM considers how the features interact with each other, Naïve Bayes treats each feature as independent.

Table 7 indicates that the scores for most techniques are similar to each other, except for Naïve Bayes. This is because Naïve Bayes treats each data point as independent, ignoring their relationship to each other. In the LPT section, only fatigue and creep damages are considered due to the possibility of overfitting. Unlike other sections, it is known beforehand that overfitting will occur on damages in the LPT section, prior to the start of the machine learning algorithm.

Table 7. Accuracies for LPT

	Fatigue	Creep	Mean
LR	.95	.95	.95
KNN	.95	1	.975
SVM	.95	1	.975
KernelSVM	.95	1	.975
Naive Bayes	.9	.9	.9
Decision Tree	.95	1	.975
Random Forest	.95	1	.975

In general, SVM has the highest average score of 0.957, or 95.7%. This suggests that the machine learning algorithms were effective in detecting gas turbine damages, achieving high accuracy across all areas. In contrast, Naïve Bayes has the lowest score of 0.8685, or 86.85%. Although this score may be acceptable in other industrial applications, in the energy or aviation sectors, it could lead to catastrophic events.

4 Conclusion

The study showed that machine learning algorithms can accurately detect deterioration in turbomachine parts, with the Support Vector Machine method having the best overall accuracy. This is significant as traditional damage control procedures can be time-consuming and may miss undetected damage, posing risks in the future. Machine learning algorithms offer a way to achieve high accuracy, which can ultimately improve the safety and reliability of turbomachines.

This development is particularly relevant in the aviation industry, where safety is paramount. However, there is a concern that false positive errors could have catastrophic consequences, which may be due to the lack of access to real data. Further research and development could improve the algorithm and reduce the costs and time required for maintenance periods, especially in aviation.

Despite these challenges, the energy sector is expected to benefit from this development as the algorithm could reduce the time needed for damage detection during maintenance work, allowing businesses to resume operations sooner. This could potentially increase their profit margins by reducing downtime and revenue loss.

Overall, the study demonstrates the potential of machine learning algorithms in the field of turbomachines, with further research and development leading to even more effective methods for detecting damage and deterioration. While there are still challenges to overcome, the benefits of this development in the energy and aviation industries are significant.

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