
Comparative Analysis of Machine Learning Models for Predictive Maintenance in Aviation: A British Airways Case Study

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Abstract

This study investigates the design and application of a predictive maintenance decision-making system for the aviation industry, using British Airways as a case study. It explores how big data analytics and machine learning techniques can transform traditional maintenance approaches from reactive and scheduled methods to proactive, condition-based strategies. The research employs a quantitative methodology, utilising a dataset containing aircraft operational parameters such as temperature, pressure, usage, and event indicators. Data preprocessing, feature selection, and model development were conducted using multiple regression-based algorithms. The results demonstrate that the Random Forest Regressor outperforms other models in predicting potential failures, showing superior accuracy across key performance metrics. This indicates its suitability for real-time predictive maintenance applications. The study highlights the potential of integrating such models into airline operations to reduce downtime, optimise maintenance scheduling, and improve aircraft reliability. Despite challenges related to data quality, cost, and implementation complexity, the research concludes that predictive maintenance systems can significantly enhance operational efficiency, safety, and cost-effectiveness in the aviation sector.

Keywords: Predictive Maintenance, Machine Learning, Algorithm, Big Data Analytics Aviation Industry

1. Introduction

Predictive maintenance in aviation involves using data and analytics to predict when an aircraft component is likely to fail so that maintenance can be performed just in time to prevent the failure (Daily & Peterson 2017). Instead of following a fixed schedule, maintenance is scheduled based on the actual condition of the aircraft. This approach helps optimise maintenance activities, reduce downtime, and increase the overall efficiency of aircraft operations (Samaranayake & Kiridena 2012). By monitoring various parameters such as engine performance, vibration levels, and other critical factors, airlines can anticipate potential issues and address them before they lead to unplanned maintenance events or failures (Fei, *et al* 2020).

The aviation industry faces unprecedented challenges, including the escalating complexity of aircraft systems, the need for stringent safety standards, and the pressure to minimise downtime and associated costs (Gorodnicka & Alomar 2022). Traditional maintenance approaches, such as scheduled and corrective maintenance, are no longer sufficient to meet these challenges. The introduction of big data technologies has enabled the aviation industry to transition from reactive to proactive maintenance strategies (Odarchenko *et al.*, 2019).

The importance of predictive maintenance in the aviation sector cannot be overstated. As aircraft systems become more sophisticated, there need to address potential failures before they occur is critical. Predictive maintenance leverages advanced analytics, machine learning algorithms, and real-time data from various sensors present in aircraft components to forecast equipment failures and prescribe timely interventions (Bhanji *et al.*, 2021). This proactive approach not only minimizes unplanned downtime but also contributes to substantial cost savings by optimizing the utilization of resources and extending the lifespan of critical components.

The utilization of big data in predictive maintenance introduces a multifaceted dimension to decision-making processes (Bousdekis *et al.*, 2021). This study explores the integration of diverse data sources, ranging from sensor data and historical maintenance records to weather patterns and flight data, in creating a comprehensive decision-making framework. By harnessing the vast amounts of data generated during the entire lifecycle of an aircraft, British Airways can gain unprecedented insights into the health of its fleet, enabling data-driven decisions that enhance safety, reliability, and overall operational efficiency.

Theoretical frameworks underpinning this study include the application of machine learning algorithms, predictive analytics models, and decision support systems. Drawing on established theories in the fields of data science, operations research, and aviation management, this study seeks to develop a robust conceptual framework that aligns with the unique challenges and objectives of British Airways.

The aviation industry's margins are famously thin, with airlines continuously seeking ways to improve efficiency, reduce costs, and enhance safety. Scheduled maintenance often results in ground time for aircraft, leading to potential revenue loss. Unplanned maintenance, on the other hand, can result in costly disruptions (Talari & Awasthi, 2015). By developing a predictive maintenance system backed by big data analytics, British Airways can significantly enhance operational efficiency, reduce maintenance costs, and ensure higher standards of safety. This study is not just crucial for British Airways but can set a precedent for the global aviation industry, showing how legacy systems can evolve by integrating modern data science techniques. Moreover, this study can bridge the gap between theoretical big data applications in predictive maintenance and real-world scenarios in the aviation sector, offering insights, methodologies, and frameworks that can be replicated across industries.

The study presents an approach to enhance aircraft maintenance operations. However, it is important to acknowledge certain limitations associated with this study. Firstly, the research heavily relies on the availability and quality of big data, which may be subject to inaccuracies, missing data, or data inconsistencies. These issues can potentially affect the reliability and effectiveness of the predictive maintenance system (Smith & Jones 2019). Moreover, the study's generalizability may be limited, as the research focuses specifically on British Airways and its unique operational environment. The findings may not be directly applicable to other airlines with different fleets, maintenance practices, and data infrastructures. Furthermore, the adoption and implementation of such a system may entail substantial costs and require considerable technological expertise, which may not be feasible for smaller airlines with limited resources. Finally, ethical and privacy concerns related to the collection and use of passenger and maintenance data should be considered, as they may impose regulatory and public acceptance challenges. These limitations underscore the need for a careful and context-specific consideration of the proposed predictive maintenance system within the broader aviation industry. The aim of this study is to design and conceptualize a predictive maintenance Decision-making system for British Airways using big data analytics.

Predictive maintenance has emerged as a critical strategy for optimizing the performance and reliability of industrial equipment and infrastructure. In recent years, the integration of big data analytics into predictive maintenance processes has garnered significant attention (Ribeiro, A., *et al.*, 2018).

One fundamental aspect of predictive maintenance is the early detection of equipment failures and the ability to perform maintenance activities before costly breakdowns occur. Big data analytics provides a promising avenue for achieving this goal. Zhang, L., *et al* (2018) emphasize the importance of big data in predictive maintenance by highlighting its capacity to harness large volumes of data from sensors and other sources. These data sources enable the creation of robust machine learning models that can predict equipment failures with high accuracy, ultimately reducing downtime and maintenance costs (Jans, R., *et al* 2018).

The integration of big data analytics in predictive maintenance is well-documented in the manufacturing industry. Wang *et al.* (2017) demonstrate that utilizing big data-driven predictive maintenance can result in a substantial reduction in maintenance-related expenses, with the potential for savings reaching up to 30%. By leveraging historical data and real-time sensor information, industries can establish proactive maintenance routines, ensuring that equipment remains operational and reliable.

While the benefits of big data in predictive maintenance are clear, it is also essential to address challenges associated with data quality, security, and scalability. Chen, D. *et al.* (2018) stress that organizations must invest in data cleansing and cybersecurity measures to ensure that the data utilized in predictive maintenance is accurate and secure.

The role of big data in predictive maintenance is undeniably transformative. It empowers industries to shift from reactive maintenance strategies to proactive, data-driven approaches, thereby enhancing reliability and reducing operational costs.

Predictive Maintenance in the Aviation Industry has emerged as a critical paradigm shift in aircraft maintenance strategies. Traditionally, aviation maintenance has been primarily reactive or scheduled at fixed intervals, which often results in unnecessary downtime and increased operational costs. The advent of advanced data analytics and sensor technologies has enabled a more proactive approach, allowing maintenance to be performed precisely

when needed, thereby reducing unplanned downtime and optimizing aircraft availability. Researchers have explored various predictive maintenance techniques, including the use of data from onboard sensors, historical maintenance records, and machine learning algorithms to predict component failures with remarkable accuracy. Studies such as those by Widodo *et al.* (2019) and Guo *et al.* (2020) have demonstrated the efficacy of predictive maintenance in improving the reliability and safety of aircraft operations, as well as reducing maintenance-related expenses. Furthermore, the integration of predictive maintenance into aviation industry practices is also being driven by regulatory bodies, such as the Federal Aviation Administration (FAA) in the United States, who recognize the potential for enhancing safety and efficiency through this approach (FAA, 2021). As the aviation industry continues to adopt and refine predictive maintenance strategies, the sector is poised for significant improvements in operational reliability and cost-effectiveness.

Decision-making systems are integral to the field of aviation maintenance, playing a vital role in guaranteeing the safety and dependability of aircraft operations. Early approaches to maintenance decision-making primarily relied on human expertise and manual inspections. However, with the advent of advanced technologies, such as Condition-Based Maintenance (CBM) and Predictive Maintenance (PDM), the industry has witnessed a shift toward data-driven, proactive strategies (Kharouf, 2013). These systems leverage sensor data, historical records, and machine learning algorithms to predict equipment failures and prescribe maintenance actions, thus reducing downtime and operational costs (Gupta, 2018). Additionally, the integration of data analytics and Artificial Intelligence (AI) has further enhanced the capabilities of decision-making systems, allowing for real-time monitoring, fault detection, and optimized resource allocation (Singh *et al.*, 2020). While these advancements have undoubtedly improved maintenance efficiency and safety, they also bring forth challenges related to data quality, system reliability, and the need for skilled personnel to interpret and act upon the system outputs (Buchholz *et al.*, 2019).

The application of machine learning algorithms in aviation has garnered increasing attention in recent years, revolutionizing various aspects of the industry. One key area where machine learning has made significant contributions is in predictive maintenance. By analysing vast amounts of historical data on aircraft components and systems, machine learning algorithms can detect patterns indicative of potential failures, allowing for proactive maintenance interventions and minimizing unplanned downtime (Korvesis, P. 2017). Another critical domain is flight safety, where machine learning models can analyse diverse data sources, such as weather patterns, air traffic, and pilot behaviour, to identify potential risks and enhance decision-making processes. Furthermore, machine learning plays a pivotal role in optimizing route planning and air traffic management, leading to more efficient operations, reduced fuel consumption, and minimized environmental impact (Korvesis, P. 2017). As aviation continues to embrace digital transformation, the integration of machine learning algorithms holds great promise for improving overall efficiency, safety, and sustainability.

Predictive maintenance systems have emerged as instrumental tools for optimizing asset management and reducing operational costs across various industries. However, the successful implementation of these systems is not without its challenges. One primary challenge lies in ensuring the quality and availability of data, as accurate predictions heavily depend on the reliability of input data (Wang *et al.*, 2018). Data integration and interoperability present additional hurdles, requiring standardized protocols and collaborative efforts to seamlessly integrate diverse data sources (Jardine *et al.*, 2019). The upfront costs associated with implementing predictive maintenance systems, encompassing sensor acquisition, analytics tools, and infrastructure, pose economic challenges for organizations

(Parida *et al.*, 2019). Addressing the skill gap in the workforce, particularly in data analytics and machine learning, is crucial for successful deployment (Zhang *et al.*, 2020). Organizational resistance to change, especially from maintenance teams accustomed to traditional practices, hinders adoption and necessitates effective change management strategies (Eriksson *et al.*, 2017). Furthermore, concerns about cybersecurity threats and ensuring regulatory compliance add layers of complexity to the implementation process (Wang *et al.*, 2017). Finally, achieving scalability and flexibility in predictive maintenance systems, especially amid fleet expansions and technological advancements, remains a persistent challenge (Zeng *et al.*, 2021). Addressing these challenges requires a comprehensive approach that encompasses technological innovation, organizational adaptation, and strategic planning.

Established in 1974, British Airways (BA) serves as the prominent flag carrier and the largest airline in the United Kingdom. Acknowledged for its dedication to service excellence and innovation, British Airways has significantly contributed to shaping the global aviation industry (British Airways, 2022). British Airways has a rich history that traces its roots back to the merger of two iconic airlines, British Overseas Airways Corporation (BOAC) and British European Airways (BEA). This merger resulted in the formation of British Airways on March 31, 1974. Over the decades, the airline has consistently adapted to changing market dynamics, incorporating technological advancements, and expanding its global footprint (<https://www.bbc.com/news/business-52769129>). With a diverse fleet of aircraft, including the iconic Boeing 747s and the modern Airbus A380s, British Airways connects passengers to over 200 destinations worldwide. The airline's extensive network spans Europe, North America, Asia, Africa, and Australia, making it a crucial player in international air travel (<https://www.britishairways.com/en-gb/information>). British Airways is synonymous with exceptional service. The airline has invested significantly in enhancing the passenger experience, from luxurious lounges to in-flight services. The introduction of the Club World business class and First-Class cabins exemplifies the commitment to providing top-tier travel experiences (<https://www.britishairways.com/en-gb/information/about-ba/first>). Adopting a pioneering spirit, British Airways has been at the forefront of aviation technology. The implementation of digital solutions, such as online check-in and the use of biometric technology, has streamlined processes for passengers. Additionally, the airline has embraced environmental responsibility by investing in fuel-efficient aircraft and exploring sustainable aviation fuel options (<https://www.britishairways.com/en-gb/information/about-ba/club-world>). The aviation industry is not without challenges, and British Airways has faced its share. Economic downturns, geopolitical uncertainties, and the global pandemic have all posed significant hurdles.

However, the airline's resilience has been evident in its strategic initiatives, cost-saving measures, and adaptability to evolving circumstances (<https://www.britishairways.com/en-gb/information/about-ba/sustainability>). British Airways recognizes its role in society and actively engages in corporate social responsibility (CSR) initiatives. From community projects to environmental conservation efforts, the airline strives to make a positive impact beyond its core business operations.

2. Methodology

The study adopts a quantitative research methodology to evaluate the effectiveness and feasibility of implementing a predictive maintenance system within the operational context of British Airways. This approach is particularly suitable given the data-intensive nature of predictive maintenance, where large volumes of structured and semi-structured data are analysed to uncover patterns, relationships, and predictive insights. The research utilises

historical aircraft maintenance records, operational parameters, and performance indicators to support the development of predictive models aimed at enhancing maintenance decision-making processes.

The methodological framework begins with data acquisition, drawing on a publicly available predictive maintenance dataset obtained from Kaggle. The dataset comprises multiple operational variables, including temperature, pressure, usage, censoring status, and recorded events. These variables represent key indicators of aircraft system conditions and usage patterns, forming the foundation for predictive modelling. The dataset consists of thousands of observations, providing sufficient granularity to support robust statistical and machine learning analyses.

Following data collection, preprocessing procedures are implemented to ensure data quality and consistency. This involves handling missing values, identifying and removing outliers, and transforming variables into suitable formats for analysis. In particular, categorical and textual variables are encoded into numerical representations to enable compatibility with machine learning algorithms. Data normalization techniques are also applied to standardize the range of numerical features, thereby improving model performance and stability.

Feature selection constitutes a critical stage in the methodology, where the most influential variables affecting aircraft health and maintenance requirements are identified. Statistical techniques, including regression analysis, are combined with machine learning-based feature importance measures to determine the relative contribution of each variable. This process ensures that only relevant and meaningful features are included in the model, thereby reducing complexity and enhancing predictive accuracy.

Subsequently, predictive models are developed using a range of machine learning algorithms suitable for regression-based predictive maintenance tasks. These models are trained on historical data to learn underlying patterns and relationships between operational variables and failure events. The training process involves splitting the dataset into training and testing subsets, allowing for the evaluation of model performance on unseen data. Cross-validation techniques are further employed to ensure the robustness and generalizability of the models.

The system architecture is designed as a modular framework, integrating key components such as data acquisition, preprocessing, feature selection, model training, and prediction. This modular design facilitates scalability, flexibility, and ease of integration with existing maintenance systems. Each module operates in a coordinated manner to enable seamless data flow and efficient processing, ultimately supporting real-time or near real-time predictive capabilities.

To ensure long-term effectiveness, the methodology incorporates mechanisms for continuous monitoring and system updating. Feedback loops are established to capture performance metrics and user input from maintenance personnel, enabling iterative refinement of the predictive models. Regular updates and retraining processes are conducted using newly available data to maintain model accuracy and relevance in dynamic operational environments.

The data processing phase further involves exploratory analysis to understand data distributions, relationships, and potential imbalances. In this study, specific attention is given to class imbalance within certain variables, which can adversely affect model performance. Resampling techniques are applied to address this issue, ensuring a balanced representation of classes and improving the reliability of predictive outcomes. Correlation analysis is also

conducted to examine relationships among variables, guiding the selection of appropriate algorithms that are robust to multicollinearity.

A range of machine learning algorithms is employed to evaluate predictive performance, including linear regression, ridge regression, lasso regression, decision tree regression, random forest regression, and support vector regression. These algorithms are selected based on their suitability for handling structured data and their proven effectiveness in predictive maintenance applications. Model performance is assessed using standard evaluation metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared, and Mean Absolute Percentage Error (MAPE), providing a comprehensive assessment of predictive accuracy and reliability.

Overall, the methodology provides a structured and data-driven approach to developing a predictive maintenance decision-making system. By integrating advanced analytics, machine learning techniques, and a modular system design, the study establishes a robust framework capable of supporting proactive maintenance strategies within the aviation industry.

3 ANALYSIS AND RESULTS

3.1 Data Analysis

Data analysis is conducted to determine the distribution and correlation coefficient of some variables before using them in a machine learning algorithm. It is essential to carefully analyse the data, select appropriate features, and choose suitable algorithms based on the characteristics of the dataset. It allows one to make informed decisions about data transformations, outlier handling, and model selection, ultimately contributing to the overall success of the machine learning process. However, assessing the correlation coefficient is a useful initial step in understanding the characteristics of your dataset and making informed decisions about feature selection and model building. It helps to understand the relationships between variables.

Data Information

```
<class 'pandas.core.frame.DataFrame'>
```

RangeIndex: 7456 entries 0 to 7455

Data columns (total 5 columns):

Table 3. 1: Data Frame

#	Column	Non-Null Count	Dtype
0	usage	7456 non-null	bool
1	Temperature	7456 non-null	float64
2	Pression	7456 non-null	float64
3	Censored	7456 non-null	bool
4	Event (fail or censored)	7456 non-null	object

dtypes:bool(2)float64(2), object(1)

memory usage: 189.4KB

Table 3. 1: Data Frame

This Data frame above in Table 3.1 capture information about various parameters and events. Below is the breakdown of the columns:

1. Usage: This column is of boolean type ('bool') and indicates whether the aircraft has been in use. A value of 'True' suggests that the aircraft has been in operation, while 'False' indicates non-usage.

2. Temperature: This column is of type float (`float64`) and represents the temperature associated with the aircraft. Temperature can be a critical factor in predictive maintenance, as extreme conditions may impact the performance and integrity of aircraft components.

3. Pression: This column is also of type float (`float64`) and represents pressure associated with the aircraft. Pressure can be another crucial parameter in aircraft maintenance, as it affects various systems and components.

4. Censored: Another boolean column (`bool`), it indicates whether the data is censored or not. Censoring is a term commonly used in survival analysis, and in the context of predictive maintenance, it might mean that certain data points are not fully observed or are incomplete.

5. Event (fail or censored): This column is of type object, possibly containing strings. It represents whether an event has occurred (e.g., failure) or if the data is censored. This column may be vital for classification or regression tasks related to predicting maintenance events.

In the context of predictive maintenance for aircraft, the Data frame captured information about the usage patterns, environmental conditions (temperature and pressure), and the occurrence of events or censoring. The use of boolean columns suggests that the dataset may be suitable for binary classification tasks. No null values, therefore, the dataset is clean.

Memory Usage: The Data frame consumes approximately 189.4 KB of memory.

3.2 Analysis of correlation Between Variable in the Dataset

The figures below show analysis of relationships between variables in the dataset before they are used in machine learning algorithms.

The relationship shows no correlation between the two variables. This relationship will not affect the ability of a machine learning algorithm to make predictions, because different machine learning algorithms have varying degrees of sensitivity to the correlation structure in the data. Suitable algorithms are chosen based on the relationship between this two variables temperature and pressure in this dataset.

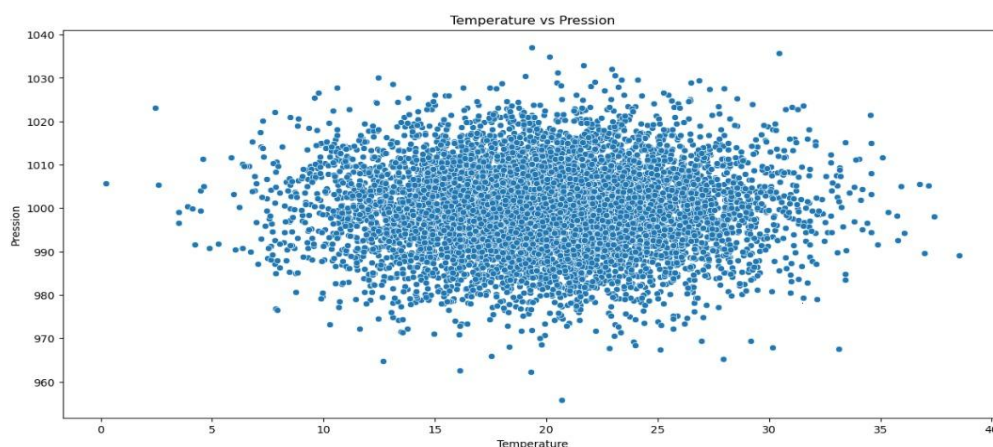


Figure 3. 1: Chart showing the relationship between temperature and pression.

Figure 3.2 below shows the distribution of censored before resampling. The data in this case appears to be imbalanced with an overwhelming False majority accounting for more than 95% of the data. Imbalance data can significantly affect the performance of machine learning algorithms. It can lead to various challenges and issues for machine learning models. To address this issue, we apply resampling technique.

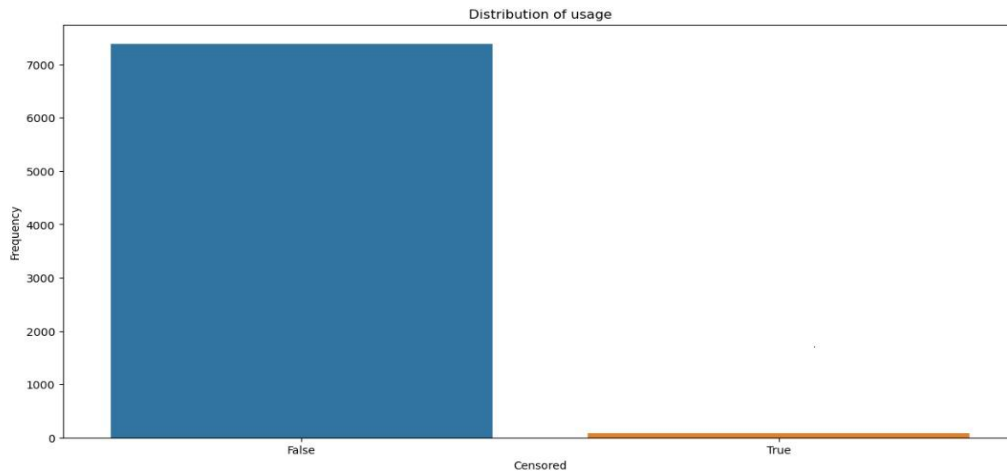


Figure 3. 2: Chart showing the distribution of censored before resampling.

The figure 3.3 below shows the distribution of censored after resampling. The data in this case appears to be balanced with an equal value of False and True. Therefore, this variable will not affect the performance of machine learning algorithms.

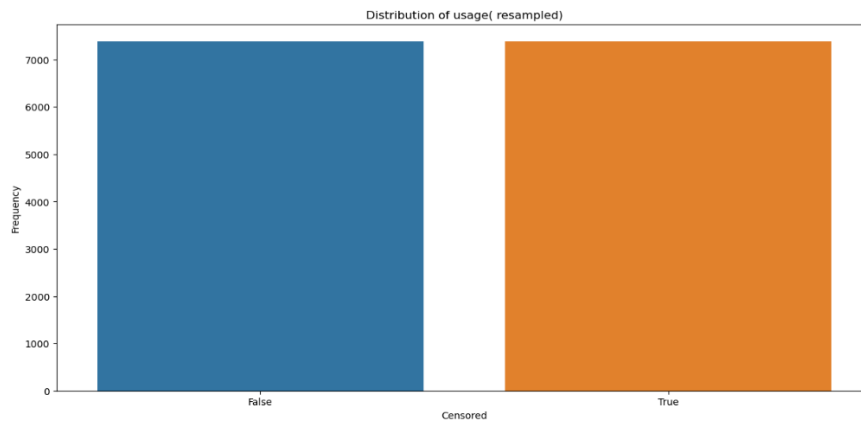


Figure 3.3: Chart showing the distribution of censored after resampling.

The chart in figure 3.4 shows a heatmap presenting the correlation coefficients between various variables in the dataset.

From the values seen in the figure, it is observed that not much correlation is seen amongst any of the pair of variables in the dataset. This relationship will not affect our prediction because algorithms that are less sensitive to linear correlation are chosen.

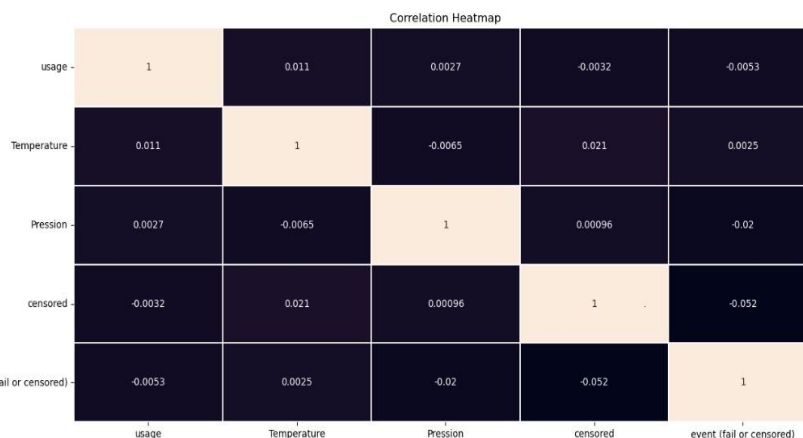


Figure 3.4: Chart showing the correlation coefficients between various data points.

3.2 Presentation of Result

Several steps were taken on the data processing for this dissertation to achieve result. First, a comprehensive dataset was collected, which are Temperature, Pressure, Censored, Event and Usage which constitute the independent variables. The dataset was then cleaned to address missing values and outliers. Exploratory Data Analysis (EDA) was performed to gain insights into the distribution and relationships between variables. Feature engineering is performed to extract relevant features that contribute significantly to predictive maintenance decisions. This step is crucial for improving the performance of the predictive model.

The data is then split into training and testing sets. The training set is used to train the Linear regression models, while the testing set is employed to evaluate the model's performance and generalization to unseen data. Cross-validation techniques were also applied to assess the strength and quality of the model.

Temperature, Pressure, Censored, Event and Usage which constitute the independent variables was employed to the algorithm to achieve the required dependent variables which are reduction in unplanned maintenance incidents, improvement in aircraft reliability and Minimization of downtime for maintenance.

Codes for data processing, data analysis and machine learning were written to obtain the most suitable model for predictive maintenance with the use of python software tool.

The table below presents the result of the machine learning algorithm for the Dataset

Table 3.2: Result of the machine learning algorithm for the Dataset.

MODEL	Mean Squared Error	Mean Absolute Error	R-Squared	Mean Absolute Percentage Error
Linear Regression	15600.216349	103.107314	0.092452	0.873767
Ridge	15600.244427	103.107651	0.092451	0.873784
Lasso	15624.596346	103.231652	0.091034	0.877472
Decision Tree Regressor	23763.028377	101.768643	0.038242	0.682976
Random forest Regressor	13643.083925	81.583751	1.000000	0.636919
Support Vector Regressor (SVR)	15277.853804	99.813378	0.111206	0.777683

Judging from the metrics, it is evident that the Random Forest Regressor stands out as the top-performing model for this particular dataset. It consistently exhibits the lowest values across Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), coupled with the highest R-squared value. The Random Forest model's exceptional performance can be attributed to its well-acknowledged versatility and capacity to adeptly manage intricate relationships within the data.

4.3 Implementation of Result by the British Airways

A Random Forest Regressor model which emerged as the best model from this research can assist British Airways in predictive maintenance by predicting the remaining useful life of aircraft components or systems, identifying potential issues before they lead to failures, and optimizing maintenance schedules.

Below is the step-by-step guide on how the Random Forest Regressor model can be applied by the British airways.

1. British airways will deploy Random Forest Regressor model into their operational environment and integrate the model into the existing maintenance system to generate predictions for each aircraft in real-time.
2. They will set up a system for monitoring model performance over time and periodically retrain the model with new data to ensure its accuracy and relevance.
3. They will integrate the model predictions into the airline maintenance workflow and use the predictions to schedule maintenance activities proactively, minimizing downtime and reducing operational costs.
4. They will ensure that the implemented predictive maintenance system complies with aviation regulations and safety standards.

Implementing the result of this research will allow British airways to move from reactive to proactive maintenance, reduce downtime, minimize operational disruptions, and optimize maintenance costs.

Choice of Programming Language

Python was used for this analysis; it is an open-source, user-friendly language known for simplicity, versatility, strong community support, and extensive libraries.

Software and Hardware Requirements

To execute the implementation, Anaconda Navigator and Jupyter Notebook 6.4.5 were installed, providing an interactive, web-based environment for efficient data analysis.

Conclusion

In conclusion, this study demonstrates the significant potential of predictive maintenance systems powered by big data analytics and machine learning in transforming aviation maintenance practices. By shifting from traditional reactive and scheduled approaches to proactive, data-driven strategies, airlines such as British Airways can enhance operational efficiency, reduce unplanned downtime, and improve overall aircraft reliability. The findings reveal that the Random Forest Regressor model provides the most accurate predictions among the evaluated algorithms, making it a strong candidate for real-world implementation. However, successful adoption depends on addressing challenges such as data quality, system integration, cost, and the need for skilled personnel. Despite these limitations, the study confirms that predictive maintenance offers substantial benefits, including cost savings, improved safety, and better resource optimisation. Moreover, this study highlights the importance of embracing advanced analytics to support smarter decision-making and sustainable operations in the aviation industry.

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