Monitoring and Prediction of Maintenance Operations for Aircraft Engines Repair

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Abstract: Accurately estimating the hours required for maintenance, repair and overhaul (MRO) operations in the aviation sector frequently depends on the experience and personal judgment of engineers, can lead to introducing errors, increased operating costs, and time-consuming decision-making. This work presents the development of a cost-effective application to monitor and predict MRO operations in an aeronautical company. The application integrates data-driven algorithms, particularly Machine Learning (ML), with Power BI to provide a dynamic and user-friendly visualisation of historical and predicted data, improving decision-making time and facilitating operational planning. The simple linear regression model was the most effective algorithm to predict MRO operation for the case study with a R^2 of 0.81, balancing simplicity and performance compared to other analysed models.

Keywords: Monitoring, Prediction, Machine Learning, Maintenance, Aircraft Engines.

1. INTRODUCTION

The aviation sector is suffering a worldwide shortage of parts and skilled labour, consequently increasing the waiting times for the engine maintenance, repair and overhaul (MRO), expected to peak in 2026 (Harris and Sion, 2024). Currently, the turnaround time for new-generation engines is 150% higher than pre-pandemic times and 35% higher for legacy engines, with the pressure on the aircraft engine maintenance companies increasing each day (Harris and Sion, 2024). The MRO processes receive significant attention as they represent one of the highest costs, accounting for 10% of an airline's total operating costs (Tsakalerou et al., 2022). These factors have increased the pressure on engineers to plan and accurately predict engine maintenance times.

Traditionally, prediction relies heavily on the lead engineer's expertise, often leading to errors such as underestimating the required time due to lack of knowledge, variability in the technicians' skill levels, and poor communication between technicians and planners (Chatzi et al., 2019). The digitalisation of systems using Industry 4.0 technologies has increased the need for advanced monitoring and prediction based on data analytics (Duan and Xu, 2021). In particular, predictive maintenance plays a crucial role in the maintenance sector by optimising processes, managing maintenance schedules, and predicting operations and their duration (Compare et al., 2020).

In this context, there is a need for developing advanced approaches to monitor and predict the duration of maintenance operations more accurately, minimising errors and enhancing overall efficiency (Achouch et al., 2022). Most of the approaches applied to the maintenance of aircraft engines are employed to estimate the remaining useful life (RUL) (Zheng et al., 2018; Louen et al., 2013; Wu et al., 2018), performance predicting (Fentaye et al., 2021; Kurt, 2024), and fault diagnosis (Yan, 2006; Wang et al., 2012). In the case of aircraft engine maintenance scheduling, usually, optimisation algorithms are applied, e.g., multi-objective evolutionary algorithm (Kleeman and Lamont, 2005), and genetic algorithm (GA) (Wang et al., 2010). However, the prediction of the actual duration of individual maintenance tasks based on operational data, particularly through data-driven methods, has been insufficiently addressed, representing a critical gap that directly affects the efficiency of MRO processes.

This paper proposes a novel and innovative cost-effective application for monitoring and predicting MRO durations by integrating machine learning (ML) algorithms with Power BI. Unlike previous studies that focus on predictive maintenance, this research specifically predicts maintenance task durations, helping reduce scheduling errors, improve resource allocation, and minimise downtime in aircraft engine repair. The system was validated on the maintenance line of the aeronautical company OGMA, evaluating various ML algorithms to find the most effective one for predicting task durations. The results showed that a simple linear regression model offered the best balance of accuracy, efficiency, and interpretability, making it ideal for integration with Power BI. This study enables decisionmakers to make informed, real-time adjustments to maintenance schedules by combining predictive analytics with a user-friendly business intelligence platform.

The paper is organised as follows: Section 2 overviews the related work on applying monitoring and prediction approaches for MRO processes, and Section 3 presents the case study and describes the architecture of the proposed application. Section 4 describes the prediction model to estimate the duration of maintenance operation, including the data pre-processing, feature analysis, and algorithms definition. Section 5 describes the implementation of the monitoring and prediction application by embedding the ML algorithm and discussing the achieved results in terms of usability and efficiency. Finally, Section 6 summarises the conclusions and future work.

2. RELATED WORK

MRO processes in the aviation sector, especially in the aircraft engine maintenance, are crucial for ensuring the reliability, safety, and performance of the process. By applying monitoring and predictive approaches to MRO processes, airlines can make proactive decisions, reduce unplanned downtime, and enhance operational efficiency. A crucial approach in this context is the prediction of the Remaining Useful Life (RUL) of components, which is essential for optimising scheduling maintenance, preventing unexpected failures, and reducing downtime. Several studies have explored the use of ML algorithms to predict the RUL of aircraft engines. Zheng et al. (2018) proposed a data-driven approach that combines the Time Window (TW) and the Extreme Learning Machine (ELM) algorithm to predict RUL values for aircraft engines. Louen et al. (2013) used Support Vector Machines (SVM) along with the Weibull reliability function for RUL prediction, while Wu et al. (2018) applied Long Short-Term Memory (LSTM) neural networks for the same purpose. These studies highlight the effectiveness of RUL prediction methods in enabling proactive maintenance scheduling and preventing catastrophic failures.

In addition to RUL prediction, performance monitoring and fault diagnosis are crucial in efficient engine maintenance. Early fault detection and performance assessment during different flight phases can prevent serious issues and ensure operational safety. Fentaye et al. (2021) proposed the use of Modular Convolutional Neural Networks (CNN) for fault detection, while Kurt (2024) employed Gaussian Process Regression (GPR), SVM, and multilayer perceptron models to predict engine performance during takeoff. Additionally, Yan (2006) developed a fault diagnosis system using Random Forest, and Wang et al. (2012) proposed an SVM-based system for both online and offline engine diagnosis and prognosis. These advancements in fault diagnosis contribute to the early identification of issues, enhancing the reliability of systems.

Moreover, scheduling aircraft engine maintenance is also an area where predictive techniques can offer significant benefits. Most existing approaches rely on optimisation algorithms to solve scheduling and resource allocation problems. Kleeman and Lamont (2005) applied a multi-objective genetic algorithm (MOEA) to solve engine maintenance scheduling issues, while Wang et al. (2010) proposed a method combining the Analytic Hierarchy Process (AHP) and genetic algorithms (GA) for maintenance scheduling. These approaches help optimise downtime and resource requirements, making the maintenance process more efficient and cost-effective.

Moreover, ML techniques have proven to be highly effective in improving operational efficiency in MRO activities. Chidinma et al. (2022) applied Natural Language Processing (NLP) to classify unstructured fault log data, significantly enhancing troubleshooting processes in MRO operations. Pebrianti et al. (2024) proposed the use of CNNs for predictive maintenance, developing an alert system that assists engineers and maintenance technicians in preparing for future repair procedures. Nguyen and Medjaher (2019) developed a model using LSTM networks to account for imperfect prognostics, emphasizing the importance of accurate predictive maintenance to ensure operational reliability. Additionally, Rosell et al. (2023) described a machine learning-based system utilizing the U-Net deep learning model to automate defect identification in aerospace manufacturing, where operators assist the system by approving results, thus refining the ML algorithm.

However, while these advancements have significantly improved maintenance practices, most applications of monitoring and prediction in aviation primarily focus on the field of PdM, by predicting the RUL of components, assessing performance, and diagnosing faults. There is still a notable gap in predicting the duration of repair operations, particularly for complex tasks such as aircraft engine maintenance. This gap represents a critical challenge, as predicting repair durations is essential for better resource allocation, reducing downtime, and minimising costs associated with MRO activities. Closing this gap is crucial for improving operational efficiency and reducing operational costs by providing a more precise view of the time required to complete maintenance tasks efficiently.

3. CASE STUDY AND SYSTEM STRUCTURE

This section presents the case study and the system architecture to integrate data visualisation and prediction of the duration of repair operations in aircraft engines.

3.1 Case Study

The case study is related to the engine maintenance process applied by the OGMA, which provides MRO services for engines and components in the aeronautical sector. The process workflow is illustrated in Fig. 1.

When an aircraft engine arrives for maintenance, the engineering team assesses the engine's condition and generates work orders containing estimated hours to be executed by the maintenance team. Depending on the identified issues, the process is divided into several maintenance phases, including evaluation, disassembly, cleaning, and repair, each managed by specialised departments. Each task is further divided into smaller operations that must be completed to finalise the maintenance process.

As each operation is completed, the work orders are returned to the engineering team, allowing them to compare

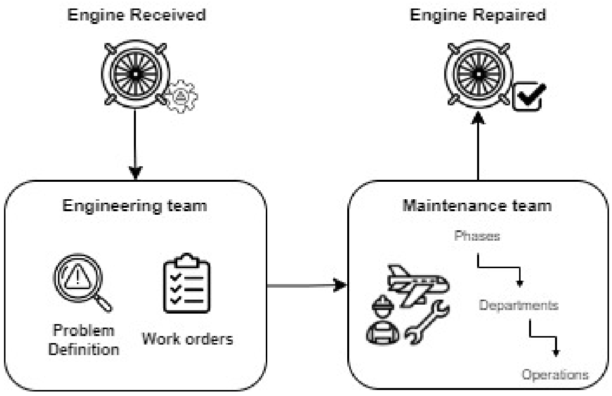

Fig. 1. Maintenance process workflow.

the initially estimated hours with the actual hours worked. An accurate estimation of the work hours is a critical part of this process, but it heavily relies on the lead engineer's experience and judgment, being a time-consuming task. The confluence of these factors makes the estimation process time-consuming, leading to errors, increased operating costs and interruptions in the maintenance process.

3.2 System Architecture

A monitoring and prediction application was developed to support a visual dashboard to facilitate the understanding of the company's historical data and work hours related to the previous maintenance operations in the aircraft engines and the predicted. Fig. 2 illustrates the system architecture for monitoring and prediction.

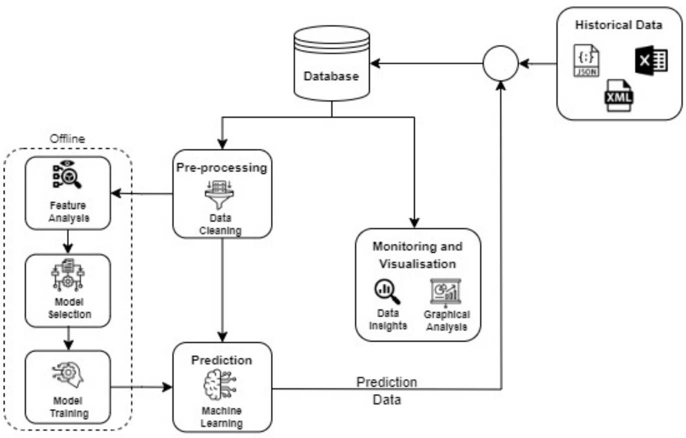

Fig. 2. System architecture for maintenance operations.

The application consists of two main components, namely the (1) Monitoring and Visualisation and the (2) Prediction. The first component enables the company to analyse trends and access critical data insights. Meanwhile, the second component comprises an ML model selected through an ML evaluation following data preprocessing and feature selection to deliver precise predictions. Both components are integrated into a central database, which stores historical and predicted data, ensuring seamless access and efficient data management and performance.

4. PREDICTION MODEL

To accurately predict working hours, it was essential to determine the most suitable algorithm for this task. For this purpose, a three-step methodology was established: (1) data pre-processing, (2) data features analyses, and (3) test different ML algorithms.

4.1 Data Pre-Processing

Data pre-processing is a critical step in implementing ML models, as it directly influences the quality and accuracy of the predictions. In this study, the CSV dataset was derived from the historical data provided by the company containing a single engine model. A cleaning process was applied to the dataset to focus on features relevant to the predictive task. The dataset comprised 23,613 rows each representing a task within the different maintenance processes, and included five columns. Four of these columns are categorical variables (FT), such as *Phase*, *Department*, *Operation*, and *Engine*, and one numerical variable (FN), the *Estimated Hours*. Given the presence of categorical variables, the One-Hot Encoding technique was applied to convert the categorical features into a binary matrix, resulting in 89 new features representing a unique category. This transformation ensures that the model treats each category independently. Additionally, normalisation was performed, ensuring that all features contribute equally to the model by maintaining consistent data scales.

4.2 Feature Analysis

The feature analysis was performed in two steps by applying the *Correlation analysis* and performing *Regularisation methods*, allowing the model to capture relevant information and minimise redundancy and overfitting.

The correlation analysis measures the strength and direction of the relationship between two features. This analysis makes it possible to identify and select the most relevant features, leading to a more simplified model with improved performance. The Pearson's correlation coefficient (PCC) was used to assess linear relationships, while the Spearman's correlation coefficient (SCC) was employed to capture both linear and non-linear monotonic relationships (Yu and Hutson, 2022). These methods enabled a comprehensive evaluation of how the selected features are correlated with the target variable.

Regularisation techniques are applied to the features to prevent overfitting and improve the model's accuracy (Shen et al., 2022). With this in mind, three linear models were applied, differing in the way that penalties are applied to the features: 1) Lasso Model (L1 Regularisation) can eliminate features that are irrelevant to the model; 2) the Ridge Model (L2 Regularisation), which reduces the complexity of the system without eliminating the features, which can be advantageous if it is necessary to keep all the variables, and 3) Elastic Net Model combines both L1 and L2 regularisation techniques, applying penalties in an intermediate way (Shen et al., 2022; Fang et al., 2023).

The correlation analysis results, summarised in Table 1, show that FN has a strong association with the target variable in both PCC and SCC correlation analyses, highlighting its significant predictive influence. In contrast, other features show correlations around 0.2, indicating weaker relationships with the target. The regularisation results align with these findings: Lasso and Elastic Net models retained only FN, underscoring its predictive strength, while the Ridge model, though retaining other features, applied substantial penalties to them. These results consistently underscore the importance of this feature in the prediction.

Table 1. Correlation and regularisation values.

Feature	**Correlation**		**Regularisation**		
	Pearson	**Spearman**	**Lasso**	**ElasticNet**	**Ridge**
FN	0.92	0.91	0.81	0.82	0.92
Others (Average)	0.02	0.04	0.00	0.00	0.03

4.3 Algorithm Selection and Evaluation

Based on Baduge et al. (2022) and Tercan and Meisen (2022), a comprehensive evaluation was conducted to choose and compare supervised regression algorithms and linear models. The models included the Simple Linear Regression, which utilises a single feature as the input; Decision Tree, which is intuitive and easy to interpret; Random Forest, which is robust against overfitting and capable of handling large datasets; Gradient Boosting, which effectively captures complex patterns through sequential learning, Support Vector Regression (SVR), which excels in high-dimensional spaces and non-linear relationships, and K-Nearest Neighbors (KNN), which is simple and effective for non-linear data but sensitive to irrelevant features. Selecting these models ensures a comprehensive data analysis that uncovers patterns and relationships that individual models may miss.

For evaluating and comparing the referred algorithms, the dataset was randomly divided into 70% for training and 30% for testing. Additionally, 10-fold cross-validation (CV) was employed to prevent overfitting in the training set. The models were evaluated according to the following criteria: R-squared (R^2), which measures the proportion of variance explained by the model; Mean Squared Error (MSE), which quantifies the average squared difference between predicted and actual values; and Mean Absolute Error (MAE), which calculates the average absolute difference between predicted and actual values.

Analysing the results of the regression models, detailed in Table 2, reveals that the KNN and Decision Tree models were less effective, producing worse results than the other models. Among the remaining models, SVR obtained the highest R^2 value (0.87), and the Simple Linear and Ridge models followed with R^2 values of 0.86. In contrast, the other models had R^2 values of 0.85, reflecting a solid overall performance.

Meanwhile, the Simple Linear model stands out with the lowest MAE (0.11), indicating superior accuracy in individual predictions. On the other hand, the Ridge and SVR models recorded the lowest MSE (0.11), highlighting their effectiveness in minimising more significant prediction errors. Despite these strengths, the differences between the SVR, Simple Linear, and Ridge models were minimal, with a variation of just 0.02 in MSE and MAE. These models effectively manage extreme values and outliers, making them suitable for prediction tasks.

Table 2. Performance metrics for the models.

Model	**Training**			**Test**			**Time (s)**
	R^2	**MSE**	**MAE**	R^2	**MSE**	**MAE**	
Simple Linear	0.86	0.13	**0.11**	**0.81**	0.26	**0.14**	**0.12**
Lasso	0.85	0.12	0.16	0.80	0.27	0.17	2.10
Ridge	0.86	**0.11**	0.13	**0.81**	**0.25**	**0.14**	0.98
Random Forest	0.85	0.14	0.13	0.79	0.28	0.15	4.68
Gradient Boosting	0.85	0.13	0.13	0.79	0.28	0.15	2.25
Decision Tree	0.83	0.15	0.14	0.78	0.29	0.15	1.86
SVR	**0.87**	**0.11**	0.13	**0.81**	0.26	0.15	46.10
KNN	0.80	0.17	0.15	0.74	0.35	0.17	0.38

Furthermore, an analysis of the final test results reveals that the models' performance was consistent with the training findings. The Simple Linear, Ridge, and SVR models achieved the highest R^2 value (0.81), with MSE values close to 0.25 and MAE values close to 0.14. This consistency highlights the models' strength in generalising beyond the training dataset, showing strong predictive accuracy. Since the algorithm will be embedded into a Power BI application, it is essential to consider computational efficiency and simplicity. In this context, the Simple Linear model stands out due to its lower complexity, as indicated by its shortest processing time (0.12s). This makes it the most suitable choice for the case study prediction, balancing accuracy and low computational demands.

4.4 Analysis of Prediction Efficiency

The predictions must be compared with the lead engineer's estimates to ensure adequate results. Fig. 3 illustrates this comparison, showing how the actual values align with both the estimates and the predicted maintenance time.

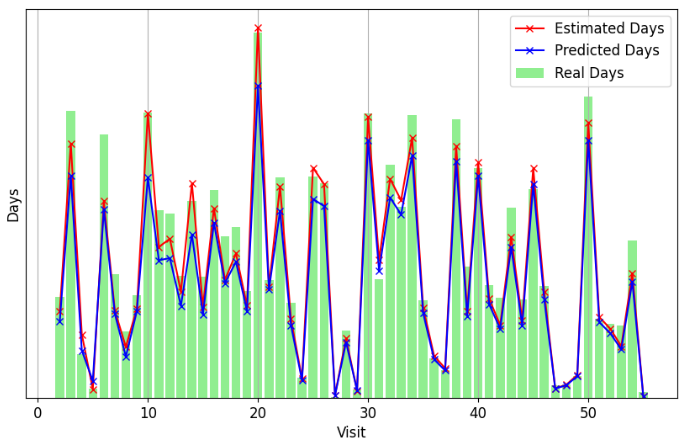

Fig. 3. Comparison of estimated, predicted and real data.

A quantitative analysis measured maintenance prediction time differences. The lead engineer's estimates had an absolute error of 2.42 days and a percentage deviation of 17.43%, while the model's predictions had an absolute error of 3.76 days and a percentage deviation of 22.13%. The model's slightly higher error is likely due to its limited dataset of just one engine model. Automating this process allows for faster and more consistent maintenance time predictions, reducing reliance on manual estimates while maintaining reasonable accuracy.

5. IMPLEMENTATION OF THE MONITORING AND PREDICTION TOOL

This section details the development of the monitoring application for the case study.

5.1 Monitoring Application

The application was developed using the Power BI platform, which allows the unification of the data, exclusively in CSV format, into an embedded database. The design of the visualisation pages focused on simplicity and clarity, ensuring that users could quickly identify trends and make informed decisions, as seen in Fig. 4 [1].

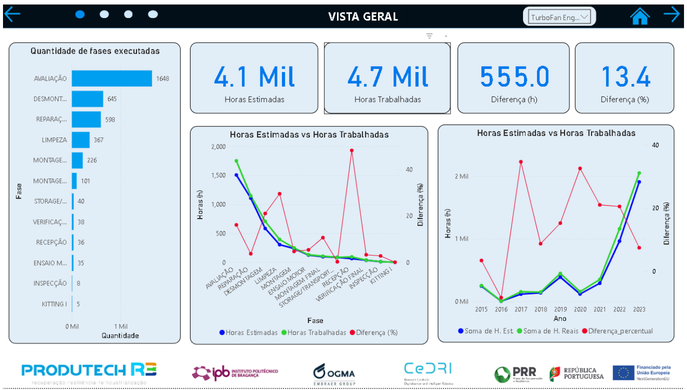

Fig. 4. Dashboard visualisation.

Moreover, **interactivity** was a key characteristic of the dashboard, enhancing user engagement and enabling deeper data exploration. Users could apply dynamic filters to focus on specific subsets of relevant data for maintenance, allowing them to click on specific data points or chart elements to access more detailed views. Furthermore, Data Analysis Expressions (DAX) were used to create custom calculations, generating deeper insights.

5.2 Embedding ML Algorithm

The Simple Linear model was chosen based on the analysis conducted in Section 4.3. It has been integrated into the Power BI dashboard through a Python script, which Power BI natively supports. This integration allows the script to access the model and generate predictions.

The implementation process starts with the operator selecting specific qualitative variables using Power BI's filtering capabilities, as illustrated in Fig. 5 [1]. Once these variables are selected, Power BI dynamically filters the historical dataset to create a subset in the Python script that matches the defined parameters. This approach ensures that the analysis focuses exclusively on data relevant to the operator's selection.

To generate predictions, the model was fed with an estimated maintenance time, which was derived by calculating the average of the estimates from previous maintenances within the filtered subset. This method enables the tool to predict maintenance times more accurately. In the future,

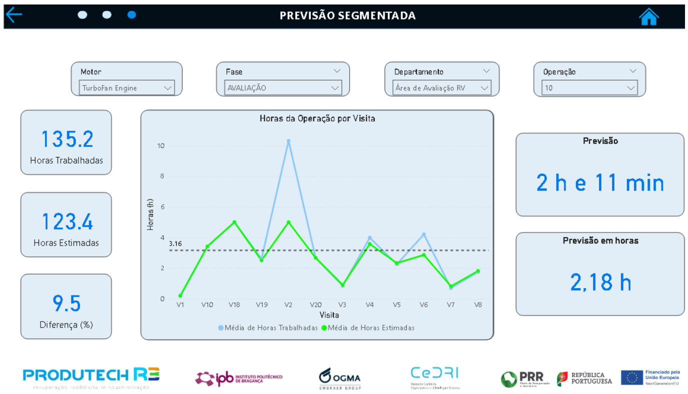

Fig. 5. Prediction visualisation.

predictions will no longer require the engineer's estimation, relying solely on the model's predictions and the actual recorded maintenance hours.

5.3 Analysis of Usability

Three average time parameters were measured using the Power BI Performance Analyser tool to evaluate the application's performance. The first parameter was the page load time, which indicated how long it took for the dashboard pages to load. The filtering load time was assessed by measuring the duration required for the dashboard to apply filters and refresh the visuals. Finally, the prediction time was evaluated using the tool to capture the total duration needed to generate predictions with the integrated Python model, including the time taken to save the results in CSV format for further analysis. The results are presented in Table 3.

Table 3. Application performance results.

Metric	Time (s)
Average Time to Load a Page	0.31
Application of Dynamic Filters	0.16
Prediction Time	2.58

The dashboard effectively provides valuable insights while maintaining accuracy, further enhanced by the integration of ML algorithms. This integration allows for the visualisation of complex datasets, enabling more informed and efficient planning of future maintenance tasks.

A key limitation of using Power BI with Python scripts is that some features are restricted to the desktop version. This prevents scripts from running in the Power BI service, complicating collaboration with larger groups. Consequently, scripts must be executed locally, which offers benefits like improved analysis, manual database updates, and better data security, ultimately supporting enhanced data exploration and decision-making.

6. CONCLUSION AND FUTURE WORK

The aviation sector faces substantial challenges due to a global shortage of parts and skilled labour, leading to increased turnaround times for engine maintenance. This situation places additional pressure on maintenance teams to optimise their processes. Traditional estimation methods, which rely heavily on the expertise of lead

[1] The data presented in this document has been modified to protect the confidentiality of the company's sensitive information.

engineers, often result in errors, high operational costs, and time-consuming tasks.

This paper details the development of a monitoring and prediction solution for the maintenance sector using ML integrated with Power BI, enabling efficient and easy visualisation of historical data and predictions. The comparison between the ML models showed that the Simple Linear Regression algorithm efficiently predicted the maintenance data for the case study, with a R^2 of 0.81, standing out for its simplicity and ease of interpretation. The integration of ML and Power BI also demonstrates the potential to streamline maintenance processes by minimising planning errors and reducing wasted time.

Future work will focus on improving the accuracy of the time prediction and expand the developed system to broader datasets with more engine types. It will also focus on the qualitative aspects of the tool usage, including qualitative user feedback.

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REFERENCES

Achouch, M., Dimitrova, M., Ziane, K., and et al. (2022). On predictive maintenance in industry 4.0: Overview, models, and challenges. *Appl. Sci.*, 12, 8081.

Baduge, S.K., Thilakarathna, S., Perera, J.S., and et al. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Autom. Constr.*, 141, 104440.

Chatzi, A.V., Martin, W., Bates, P., and et al. (2019). The unexplored link between communication and trust in aviation maintenance practice. *Aerospace*, 6, 66.

Chidinma, D.N., Mishra, B.K., and Sayers, W. (2022). Fault log text classification using natural language processing and machine learning for decision support. In *14th Int. Conf. Softw. Knowl. Inf. Manag. Appl.*, 98–103.

Compare, M., Baraldi, P., and Zio, E. (2020). Challenges to iot-enabled predictive maintenance for industry 4.0. *IEEE Internet Things J.*, 7, 4585–4597.

Duan, L. and Xu, L.D. (2021). Data analytics in industry 4.0: A survey. *Inf. Syst. Front.*

Fang, P., Wang, X., Ge, J., and et al. (2023). Elastic network regression based on sobol sequence initialized lightning attachment procedure optimization. In *Proc. 14th Int. Conf. Softw. Eng. Serv. Sci.*, 252–257. IEEE.

Fentaye, A.D., Zaccaria, V., and Kyprianidis, K. (2021). Aircraft engine performance monitoring and diagnostics based on deep convolutional neural networks. *Machines*, 9(12), 337.

Harris, J. and Sion, M. (2024). Demand is soaring for commercial engine maintenance repair slots. Technical report, Bain & Company. URL `https://shre.ink/baincompany`. Accessed: 30/09/2024.

Kleeman, M.P. and Lamont, G.B. (2005). Solving the aircraft engine maintenance scheduling problem using a multi-objective evolutionary algorithm. In *Proc. 7th Annu. Workshop Genet. Evol. Comput.*, 196–198. ACM.

Kurt, B. (2024). Evaluation of aircraft engine performance during takeoff phase with machine learning methods. *Neural Comput. Appl.*, 19173–19190.

Louen, C., Ding, S.X., and Kandler, C. (2013). A new framework for remaining useful life estimation using support vector machine classifier. In *Conf. Control Fault-Tolerant Syst.*, 228–233. IEEE.

Nguyen, K.T. and Medjaher, K. (2019). A new dynamic predictive maintenance framework using deep learning for failure prognostics. *Reliab. Eng. Syst. Saf.*, 251–262.

Pebrianti, D., Khalani, Z., Rusdah, and et al. (2024). Predictive maintenance in aerospace industry using convolutional neural network. In *9th Int. Conf. Mechatron. Eng.*, 157–162.

Rosell, A., Svenman, E., Westphal, P., and et al. (2023). Machine learning-based system to automate visual inspection in aerospace engine manufacturing. In *28th Int. Conf. Emerg. Technol. Fact. Autom.*, 1–8.

Shen, B., Ma, L., Wang, J., and et al. (2022). Lasso regression based on halton sequence initialized capuchin search algorithm. In *Proc. 10th Joint Int. Inf. Technol. Artif. Intell. Conf.*, 2487–2492. IEEE.

Tercan, H. and Meisen, T. (2022). Machine learning and deep learning based predictive quality in manufacturing: a systematic review. *J. Intell. Manuf.*, 33(7), 1879–1905.

Tsakalerou, M., Nurmaganbetov, D., and Beltenov, N. (2022). Aircraft maintenance 4.0 in an era of disruptions. In *Procedia Comput. Sci.*, 121–131. Elsevier B.V.

Wang, J., Yu, T., and Wang, W. (2010). Integrating analytic hierarchy process and genetic algorithm for aircraft engine maintenance scheduling problem. In G.Q. Huang, K.L. Mak, and P.G. Maropoulos (eds.), *Proc. 6th CIRP-Sponsored Int. Conf. Digit. Enterp. Technol.*, 897–915. Springer B. H.

Wang, Z., Zarader, J.L., and Argentieri, S. (2012). A novel aircraft engine fault diagnostic and prognostic system based on svm. In *Int. Conf. Condition Monit. Diagn.*, 723–728. IEEE.

Wu, Y., Yuan, M., Dong, S., and et al. (2018). Remaining useful life estimation of engineered systems using vanilla lstm neural networks. *Neurocomputing*, 275, 167–179.

Yan, W. (2006). Application of random forest to aircraft engine fault diagnosis. In *Proc. Multiconf. Comput. Eng. Syst. Appl.*, 468–475. IEEE.

Yu, H. and Hutson, A.D. (2022). A robust spearman correlation coefficient permutation test. *Commun. Stat. Theory Methods*, 53(6), 2141–2153.

Zheng, C., Lui, W., Chen, B., and et al. (2018). A data-driven approach for remaining useful life prediction of aircraft engines. In *21st Int. Conf. Intell. Transp. Syst.*