Future Vibration Estimation Using LSTM for Condition-Based Maintenance of Aircraft Systems

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Abstract: This study presents a deep learning-based approach for enhancing Condition-Based Maintenance (CBM) strategies in aircraft systems by utilizing Long Short-Term Memory (LSTM) networks to forecast future vibration trends. Using high-resolution time-series data from the NASA IMS Bearing Dataset, the proposed LSTM model successfully captures complex temporal dependencies that characterize degradation behaviour in aircraft components. Experimental results demonstrate that the model achieves high prediction accuracy with a low Mean Absolute Error (MAE) of 0.0010, enabling timely detection of incipient faults and minimizing unnecessary maintenance interventions. Compared to traditional models, LSTM networks offer high performance in learning nonlinear patterns and maintaining predictive reliability under varying operational conditions. The integration of LSTM-based forecasting into CBM frameworks supports proactive maintenance planning, reduces lifecycle costs, and increases aircraft safety. This study contributes to the literature by validating the practical implementation of LSTM in real-world aerospace maintenance workflows, offering a scalable and intelligent solution for predictive maintenance in both civil and military aviation contexts.

1 INTRODUCTION

In modern aircraft systems, reliability and safety are important. Conventional maintenance strategies such as corrective or time-based maintenance often result in either excessive downtime or the risk of undetected failures. In contrast, Condition-Based Maintenance (CBM) offers a proactive and data-driven solution that enables timely interventions based on the actual health status of aircraft components (Choi et al., 2016).

CBM constitute a paradigm shift in aircraft engineering, promising significant enhancements in the efficiency and safety of aircraft systems. Unlike traditional maintenance strategies that rely on time-based schedules or reactive responses to mechanical failures. CBM uses real-time data to assess the ongoing health of aircraft components. This proactive approach is facilitated by the integration of advanced sensors and monitoring technologies that gather crucial information such as vibration patterns, temperature fluctuations or pressure levels (Kabashkin & Perekrestov, 2024). By analysing these data, CBM enables the timely identification of potential failures, allowing maintenance actions to be precisely aligned with the actual condition of the components. This not only prevents unnecessary maintenance interventions but also minimizes the risk of unexpected downtimes or catastrophic failures. Thereby improve the reliability and availability of aircraft systems. In the context of aircraft industry, where operational efficiency and safety are important, CBM emerges as an indispensable tool for modern aircraft maintenance strategies (Verhagen et al., 2023).

A key advantage of CBM in aircraft is integration with health monitoring systems and machine learning algorithms, which allow for fault prediction and anomaly detection. These capabilities not only increase operational efficiency but also improve flight safety by preventing failures. For example, research by Ozkat et al. showed that deep learning

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models applied to vibration sensor data on a real-time UAV can predict when it will fail and provide a critical window for preventive action (Ozkat et al., 2023).

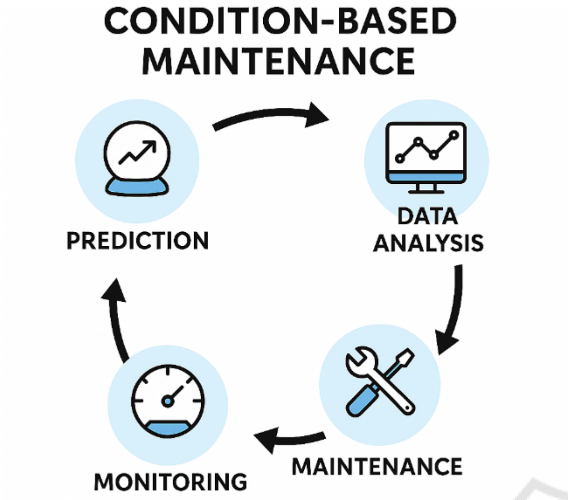

Figure 1: Schematic representation of CBM process.

Table 1: Advantages and disadvantages of RUL forecasting.

Benefits of RUL Forecasting	Challenges in RUL Forecasting
Proactive maintenance planning	Uncertainty and forecast accuracy
Prevention of unexpected failures	Complex system dynamics
Optimizing maintenance costs	Insufficient historical data
Increasing equipment availability	Impact of environmental factors
Improving spare parts inventory management	Presence of multiple failure modes
Increasing operational security	Sensor noise and errors
Efficient use of resources	Computational complexity

Moreover, CBM has been adopted in both civil and military aircraft applications, including programs such as Health and Usage Monitoring Systems (HUMS) used in helicopters and Integrated Vehicle Health Management (IVHM) systems in fixed-wing aircraft(Hünemohr et al., 2022; Scott et al., 2022). The use of CBM has led to cost savings and maintenance performance, as noted by the U.S. Department of Defense's CBM+ initiative (Department of Defense, 2024).

In summary, CBM is an innovative approach in aircraft maintenance planning. Its capacity to synchronise maintenance operations with the prevailing conditions of the system, thereby minimising the necessity for unscheduled maintenance interventions, and its ability to facilitate the implementation of predictive analytics, renders it an indispensable instrument for the future generation of aircraft safety and sustainability. The primary aim of this study is to evaluate the effectiveness of CBM applications in reducing maintenance costs and enhancing operational efficiency in aircraft systems. The necessity for such improvements stems from the limitations of traditional maintenance approaches. The utilisation of CBM allows for the synchronisation of maintenance operations with the true condition of aircraft components (Cusati et al., 2021). This approach has the potential to synchronise maintenance practices with performance requirements, thereby reducing the overall cost of aircraft operations over their lifecycle. Furthermore, the use of CBM systems has been found to enhance the operational reliability and safety of military and civilian aircraft systems. (Ernest Yat-Kwan Wong et al., 2006). The study's aim is to provide empirical evidence and insights into the cost-effectiveness and operational advantages of integrating CBM methodologies into current aircraft maintenance models.

The methodology deployed in this study uses Long Short-Term Memory (LSTM) models to analyse vibration data for CBM systems. The study focuses on the importance of predictive maintenance in aircraft, and on the capabilities of LSTM in processing time-series data, which is crucial for understanding and predicting the future states of aircraft components. LSTM networks are especially appropriate for modelling sequential data with long-range temporal correlations (Malhotra et al., 2016). The integration of LSTM models in the analysis is a key aspect of the approach, with the objective being to achieve enhanced prediction accuracy (Peringal et al., 2024).

The potential real-world implications of research on CBM within the aircraft discipline are of considerable importance. The adoption of a predictive and data-driven approach, as opposed to the traditional reactive maintenance strategy, enables CBM to implement interventions prior to the occurrence of failures. This proactive strategy has been shown to have a significant impact on maintenance costs, with a consequent reduction in aircraft downtime and enhancement of system reliability. Through the integration of CBM strategies, maintenance activities in aircraft systems can be aligned more closely with actual equipment condition, allowing for optimized scheduling, reduced downtime and increased overall mission reliability. Consequently, CBM applications offer considerable economic and operational advantages, further encouraging the thorough evaluation and advancement of predictive techniques, such as the LSTM models investigated in this study, to enhance the efficiency of these systems in real-world operational applications.

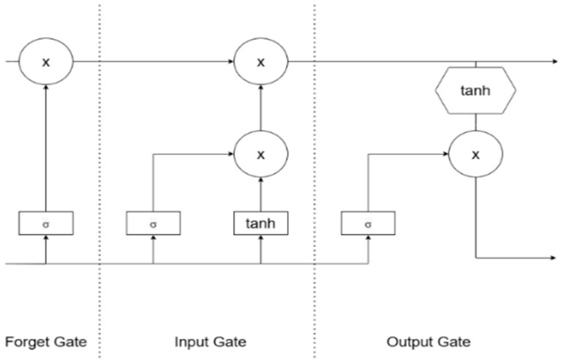

Figure 2 LTSM Neural Network Architecture.

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2 METHODOLOGY

The vibration data used in this study were obtained from the NASA IMS Bearing Dataset, a recognised standard in the field of condition monitoring research (J. Lee et al., 2007). This dataset consists of continuous vibration measurements which reflect the life cycles of bearings under applied loads. These measurements are effective in simulating mechanical degradation in real-world conditions. The high-resolution, time-series data is essential for predictive maintenance modelling. The dataset provides a robust foundation for the application of LSTM networks in estimating future vibration trends. The selection of this dataset, which includes critical failure modes, ensures that the research methodology is well-suited to address challenges in the implementation of CBM in aircraft systems.

The vibration data used in this study were obtained from a bearing test rig developed by the NSF I/UCRC Intelligent Maintenance Systems Center in the United States. The test rig consists of four Rexnord ZA-2115 double row ball bearings connected to a shaft rotating at a constant speed of 2000 RPM. A radial load of 6000 pounds (~26700 N) was applied to the shaft and all bearings were operated with a forced lubrication system. Vibration data was collected by means of high precision piezoelectric ICP accelerometers type PCB 353B33 mounted on the bearing housings. In the first data set, a total of two axes of data were collected for each bearing in the x and y axes, while in the other sets only single axis measurements were made(Qiu et al., 2006).

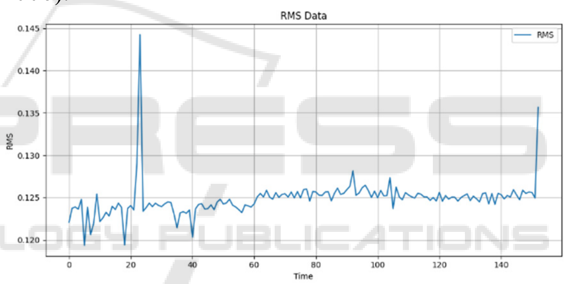

Figure 3: RMS Vibration Data for Bearing.

The preprocessing of vibration data is a critical step in preparing it for LSTM model training, and it is essential to ensure the quality and integrity of the input. Initially, the raw vibration signals from the NASA IMS Bearing Dataset are subjected to Min-Max normalization. This technique is employed to scale the data range between 0 and 1, thus helping to minimise the effects of varying scales and magnitudes, consequently enabling improved convergence during the training phase. This approach is crucial in ensuring that each feature contributes equally to the gradient descent optimisation process, thus preventing discrepancies that may arise from differing units and ranges. Following this, the normalized data is processed by generating window-based sequences, a step that configures the time-series data into a structured format suitable for LSTM input. Each sequence is characterised by a predetermined number of time steps, which are represented by a multidimensional array, thereby conforming to the LSTM's requirement for continuous temporal data inputs. The subsequent phase involves the extraction of features, with the aim of reducing the dimensionality of the data set and thereby extracting meaningful information. This process employs Root Mean Square (RMS) metrics as a means of quantifying the variability of the data. The RMS value, calculated over each time window, represents an aggregate of vibration magnitude, serving as a key indicator of bearing condition and mechanical health. By transforming the data into this comprehensive format, the preprocessing pipeline equips the LSTM model with precise and statistically comprehensive inputs, enhancing its ability to predict future vibration trends accurately.

The LSTM neural network was implemented to model time-series vibration data, thanks to its ability to identify long-range dependencies. The LSTM architecture comprises multiple layers that are designed to handle the sequence prediction tasks that are particular to the dataset. At its core, the network comprises an input layer, followed by a series of (LSTM) layers. These layers incorporate cells that are structured to retain information across time steps through gates, namely input, forget and output gates. This enables the network to effectively retain memory and learn sequences. The network uses a configuration of hidden layers comprising LSTM blocks stacked on top of each other. Each block processes a specific aspect of the temporal data (Al-Selwi et al., 2024). LSTM networks are an enhanced form of recurrent neural networks (RNNs). The hidden layer of an LSTM network has a gated unit, also known as a gated cell. The LSTM consists of four interconnected layers that produce the cell's output and cell state. These two layers are then transferred to the next hidden layer. LSTMs consist of three logistic sigmoid gates and one tanh layer.

The forget gate is crucial to an LSTM network because it discards information that is irrelevant for the current prediction context. When the gate outputs a value close to zero, the corresponding content is effectively eliminated from the cell state. Conversely, an output near one ensures that the information is retained for subsequent time steps. The input gate enables new data, relevant information to be integrated into the cell state. This selective update is derived from processed input data and modulated by a learnt weight structure. Finally, the output gate determines which parts of the current cell state are propagated to the next layer or output. This shapes the model's final prediction at that time step.

The LSTM models were trained and validated using Python as the primary programming environment and TensorFlow and Keras as the frameworks for creating and refining the neural network architecture. The LSTM model was designed using a sequential layer setup to take full advantage of Keras's high-level capabilities and streamline the implementation process. In order to prepare the network for rigorous testing, the model underwent several iterations in order to calibrate hyperparameters such as the number of hidden units, learning rate, and batch size. The Python libraries NumPy and Pandas were instrumental in the management of data operations and the facilitation of the execution of the training pipeline. Regular checkpoints were conducted throughout the iterative process to capture the model's state, guaranteeing a robust recovery procedure if necessary. The evaluation of the trained LSTM models was conducted within the same framework, using a test set that was separated at the outset of the data processing workflow to ensure the maintenance of unbiased evaluation metrics. The implementation of these methodologies ensured the establishment of a reliable predictive model capable of estimating future vibration trends with a high degree of accuracy.

The visualisation of results and the evaluation of prediction accuracy are critical components of the research methodology, facilitating in-depth analysis of the LSTM model's performance. For the purposes of this study, the Python library Matplotlib was utilised in order to create comprehensive visualisations. These tools enabled the creation of various plots, including line graphs showing predicted and actual vibration trends over time, thereby facilitating a clear visual comparison. The assessment of the model's accuracy was conducted by utilising standardised metrics, namely the mean absolute error (MAE) and the root mean square error (RMSE). These metrics offer quantifiable indicators of prediction accuracy and are imperative for the evaluation of the model's validity. The analysis was enriched with graphical plots, which highlighting the model's ability to track actual trends and identify potential inconsistencies. This information forms the basis for understanding the model's predictive capacity in real-world aircraft and space CBM scenarios.

3 RESULTS

The LSTM architecture demonstrated a strong capability in forecasting future trends in RMS vibration data, a critical aspect for the effective implementation of condition-based maintenance in aircraft systems. The network was able to process high-frequency signals obtained from the IMS Bearing Dataset effectively by leveraging its strength in modelling temporal dependencies. The system's capacity to monitor and analyse minute yet substantial variations in RMS values over time allows for the early identification of degradation indicators, often preceding the onset of apparent system failures. This predictive advantage enhances the ability of maintenance teams to initiate timely interventions, thereby contributing to improved operational safety and logistical efficiency in aircraft. Furthermore, the model enables more strategic maintenance planning by continuously monitoring vibration behaviour and providing reliable short-term forecasts. This results in minimised unnecessary servicing and optimised resource use and cost-efficiency. The enhanced performance of the LSTM model is attributable to its design, which is optimally suited to the analysis of sequential data. This model is a highly effective analytical tool for advancing condition-based maintenance in aircraft applications.

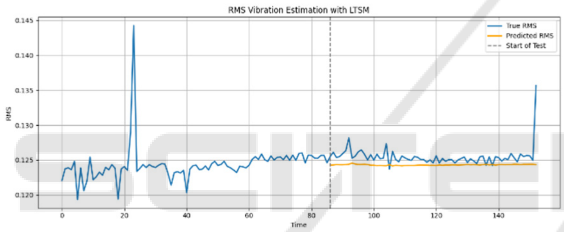

Figure 4: The prediction result used 50% as training data and 50% as test data

The LSTM model demonstrated a remarkable capacity to precisely forecast future RMS vibration trends, a capability that is of paramount importance for condition-based maintenance of aircraft systems. The model uses its realistic ability to understand complex time patterns to create a model of high-frequency vibration data from the IMS Bearing Dataset. The model's capacity to forecast alterations in RMS values over time signifies its ability to discern subtle yet substantial changes in component conditions prior to the manifestation of evident issues. The implementation of this process enables team members to engage in proactive actions, thereby facilitating enhanced safety standards and optimising operational efficiency, a particularly salient consideration within the domain of aircraft engineering and maintenance. Maintenance professionals are able to enhance their planning processes, avoid unnecessary actions, and achieve financial and temporal efficiencies by monitoring RMS trends and making accurate predictions. The LSTM model's capacity for accurate prediction is attributable to its design, which is optimally suited to the analysis of time-based data. This development indicates that the system is a powerful tool for improving condition-based maintenance in aircraft systems.

The predictive performance of the LSTM model was systematically assessed through a set of widely recognized evaluation metrics, namely MAE and RMSE. The model demonstrated a strong predictive capability, achieving a low MAE of 0.0010, which indicates high accuracy in estimating future RMSE vibration patterns in aircraft system components. Additionally, the RMSE value approaching zero reinforces this finding by reflecting minimal divergence between predicted and actual values across the time series. However, the observed R^2 value of -0.6838points to limitations in the model's ability to explain variance within the dataset, which can be attributed to the complex and highly nonlinear nature of the underlying degradation mechanisms. This discrepancy suggests that while the model is effective in short-term trend prediction, it may face challenges in modelling long-term structural variance in highly stochastic systems. These results support the model's applicability in real-world aircraft maintenance workflows, where timely and accurate predictions are essential for ensuring operational reliability and cost-effectiveness.

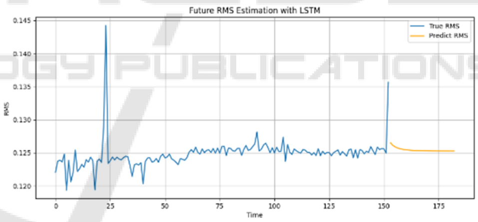

Figure 5: The prediction result used 100% as training data.

The strong ability of the LSTM network to model sequences gives it a clear advantage compared to traditional predictive models, especially in the field of condition-based maintenance. LSTM networks are explicitly designed to learn and preserve long-term dependencies through a gated memory cell architecture. This design enables them to dynamically adjust to evolving data distributions and recognize intricate vibration patterns that may precede mechanical failures. The model's robustness in such contexts is reflected in its consistently low prediction errors, even under varying operational conditions and non-uniform degradation rates. The ability of LSTM models to retain relevant historical information and update internal representations in response to new input makes them particularly effective in early anomaly detection and maintenance forecasting. Consequently, their integration into predictive maintenance pipelines represents a significant leap forward in aircraft maintenance planning, enabling data-driven, cost-efficient, and proactive interventions that improve overall system reliability and operational safety.

4 DISCUSSION AND CONCLUSIONS

This study emphasises the pivotal function of LSTM networks in optimising the execution of CBM strategies within the aircraft engineering industry. The proposed model enables high-accuracy forecasting of future vibration behaviour, thereby signifying a methodological departure from conventional maintenance practices. Conventional maintenance practices are primarily based on fixed time intervals or reactive repairs following fault detection. LSTM networks have been demonstrated to have strong capabilities in modelling nonlinear and temporally complex datasets, particularly those derived from the operational behaviour of aircraft subsystems. This facilitates the early identification of degradation patterns, thereby enabling predictive interventions to be implemented before faults evolve into critical failures. Such foresight supports maintenance strategies that are both targeted and timely, significantly reducing unplanned maintenance and improving the operational safety and reliability of aircraft in both the civil and defence industries. The findings of this research affirm that the integration of LSTM models into CBM architectures provides a data-driven and adaptive maintenance paradigm, whereby servicing actions are aligned with the real-time health status of system components. This enhanced predictive capability has been demonstrated to contribute to substantial cost savings by reducing the need for maintenance and optimising the efficiency of resource allocation within aircraft operations.

The present study aims to contribute to the literature in the field of CBM by integrating LSTM models and demonstrating the advanced capabilities of the LSTM architecture compared to traditional maintenance methods in the aircraft industry. Despite the limitations of classical regression algorithms and fundamental artificial neural network structures in capturing long-term relationships in time series, LSTM models have demonstrated notable efficacy in learning and maintaining such intricate temporal patterns. This feature facilitates more precise predictions of future vibration trends and has the potential to extend the lifespan of critical aircraft components by reducing unnecessary maintenance interventions. Analyses have demonstrated that LSTM models achieve lower MAE and RMSE values, indicating that they enhance the accuracy and reliability of CBM applications. This has been shown to result in enhanced system reliability, reduced unexpected failures and decreased maintenance costs in operational results. In conclusion, the integration of LSTM architecture into aircraft maintenance strategies is not only compatible with artificial intelligence-based predictive maintenance approaches, but also offers concrete practical gains for the maintenance optimisation of aircraft systems. This makes LSTM models optimal for the implementation of preventive, economical, and safety-focused maintenance strategies in contemporary aircraft.

This research makes a significant contribution to the academic literature by effectively bridging theoretical principles with real-world implementation practices, thereby advancing the comprehension and applicability of advanced CBM strategies in the field of aircraft engineering. The study demonstrates that the deployment of LSTM networks enhances predictive accuracy, particularly in the context of forecasting future vibration behaviours. In contrast to traditional statistical models, the proposed LSTM-based framework provides a scalable and practical foundation for real-time CBM integration. The LSTM model has been developed to learn from complex temporal sequences, thereby offering a data-driven mechanism to anticipate component-level degradation. This, in turn, has the effect of minimising redundant interventions and improving overall system availability and reliability. These findings reflect a paradigm shift from conventional predictive analytics to intelligent maintenance strategies, enabling more informed, timely and cost-effective decision-making processes. Consequently, this study addresses a critical research gap by providing empirical validation of LSTM's potential to transform CBM methodologies and establishes the foundation for future research into AI-enhanced maintenance planning in aircraft environments.

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