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Development of an Aircraft Structural Health Monitoring System for Vibration and Fatigue Analysis

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Abstract: The research focuses on the design and implementation of an integrated system to support real-time structural health assessment, specifically the Aircraft Vibration and Fatigue Monitoring System (AVFMS). The dataset employed in the study comprises 289 varying data instances recorded across different flight regimes to test the structural integrity. The primary devices employed are MEMS-based accelerators to sense high-fidelity vibrations and an ESP32 microcontroller to process data edges and transmit data wirelessly. The system identifies, at the earliest stages, signs of stress in the form of vibrations before they can develop into disastrous failures. The condition-based maintenance methodology is no longer based solely on traditional scheduled inspections; it is now more dynamic and data-driven. Results indicate that the system can efficiently differentiate between the normal operating harmonics and the abnormal stress forms. This study provides a solid technological foundation for enhancing aviation safety and extending the service life of critical airframes.

Keywords: Structural Health Monitoring; MEMS Accelerometers; ESP32 Microcontroller; Vibration Analysis; Fatigue Prediction; Aircraft Vibration; Fatigue Analysis; Artificial Intelligence.

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1. Introduction

The structural integrity of airframes is a critical subject in modern aviation, as these airframes are constantly subjected to cyclic loads and environmental stressors, as studied by Fan and Qiao [12] in their research on dynamic response evaluation of aerospace elements. The operating environment of an aircraft exposes it to constant changes in pressure, temperature, and aerodynamic forces, all of which contribute to structural degradation over time. This phenomenon is systematically investigated

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by Zacharakis and Giagopoulos [15] through integrated structural diagnostics. The old maintenance method is scheduled maintenance based on flight hours or take-off periods, a methodology that has been criticised by Ibarrola-Chamizo et al. [2] for its inefficiency in time-based inspection. The traditional approach tends to ignore the variability in operating conditions experienced by individual aircraft and, therefore, creates a gap between the assumed and actual structural health, a gap that Hou and Xia [6] critically consider in adaptive monitoring frameworks. One way to fill this gap is to develop a Structural Health Monitoring system that continuously monitors the aircraft's physical condition. Although statistical averages can provide insight into the vehicle's true condition, integrating sensors directly into the structure enables operators to assess its actual condition. A transition supported by predictive modelling techniques developed by Zahid et al. [7]. Such a paradigm shift is necessary to reduce maintenance costs and prevent sudden structural failures that can have disastrous consequences, as supported by safety-oriented studies by Sun et al. [13]. Vibration is one of the main indicators of structural change, and Lee and Eun [11] studied vibration-based methods for identifying damage caused by structural change.

The dynamic behaviour of structural elements is sensitive to the change in the material properties and boundary conditions, which mathematically is represented by Kerschen et al. [4] using nonlinear dynamic modelling methods. When a component has become worn or damaged, the natural frequency and damping characteristics are altered, thus creating quantifiable anomalies with respect to baseline conditions, a phenomenon that Quqa et al. [9] take advantage of in real-time anomaly detection systems. The ability to monitor these variations enables the detection of cracks, corrosion, or loosening of fasteners long before they can be seen, an idea that has been practically applied by Esfarjani [1] in micro-sensor-based diagnostic systems. Fatigue, the progressive structural damage that ensues when a material is subjected to cyclic loading, is also very critical and has been well examined by Katunin et al. [5] in fatigue-sensitive monitoring systems. The fatigue phenomenon in aircraft is usually the outcome of repeated cycles of cabin pressurization, aerodynamic turbulence, and landing impacts, which were experimentally simulated and analyzed by Sakaris et al. [14] to understand cumulative damage behavior. A joint analysis of vibration and fatigue monitoring helps provide a clear picture of structural health as a dual-layered fatigue protection strategy, as demonstrated by Sun et al. [13] using hybrid monitoring models. These systems also allow maintenance personnel to locate and rectify damage at its initial stages and take corrective actions in real time, thus significantly improving operating safety and system lifespan, as confirmed by Fan and Qiao [12] in their reliability assessment research. The application of MEMS technology has redefined the possibilities and scalability of Structural Health Monitoring systems, as demonstrated by Esfarjani [1] in the design of microsensor-based diagnostic systems.

These sensors are compact, low-power, and high-sensitivity. In this scenario, Quqa et al. [8] are the best choice for the embedded sensor network implementation. The miniaturisation of sensing devices enables dense arrays of sensors without substantially loading the aircraft or altering its aerodynamic characteristics, an important consideration emphasised by Katunin et al. [5] in the design of a lightweight monitoring system. In combination with microcontrollers such as the ESP32, which include built-in wireless communication and processing capabilities, the resulting system can be a very powerful platform for real-time data acquisition and remote monitoring, as demonstrated by Fritzen and Kraemer [3] in smart structural systems. The ESP32 supports smooth communication between sensor nodes and central processing units, which, in turn, enables the creation of a decentralised monitoring architecture further refined by Ibarrola-Chamizo et al. [2] for distributed sensing systems. In these architectures, the sensor node can perform some processing on the data before communicating with a central hub, reducing the computation required in the central systems and minimising communication latency, as shown in Zahid et al. [7] for wireless SHM applications. This local processing also helps improve the system's robustness, as individual nodes can continue operating even in the presence of partial network failures, a resilience characteristic that Frigui et al. [10] focus on in fault-tolerant monitoring systems. Moreover, combining MEMS sensors with sophisticated signal-processing algorithms enables the extraction of meaningful features from raw vibration and strain data. This process can be optimised by Kerschen et al. [4] through dimensionality reduction and pattern recognition algorithms.

These characteristics are then used to train machine learning models capable of detecting complex damage patterns, a methodology that Lee and Eun [11] successfully applied in automated damage classification systems. The combination of hardware innovation and algorithmic intelligence enables the development of a highly adaptive monitoring framework that responds to changing structural conditions, as shown by Hou and Xia [6] in adaptive SHM systems. This capability to constantly learn new data and update predictive models increases the accuracy and reliability of damage detection, as Sun et al. [13] found in intelligent monitoring applications) emphasizes. This integration not only enhances detection sensitivity but also reduces the number of false alarms, thereby increasing the credibility of the monitoring system among maintenance department employees and decision-makers. Finally, the objective of the proposed research is to develop a general framework for proactive and condition-based maintenance that is consistent with the modern maintenance philosophies discussed by Hou and Xia [6]. The aviation industry can increase profitability by switching from reactive, schedule-based maintenance to data-driven approaches, as quantitatively illustrated by Frigui et al. [10] in their analysis of operational efficiency. This change reduces aircraft downtime, thereby enhancing fleet availability and operational profitability, as Fan and Qiao [12] noted in their analysis of the systems' performance metrics. Also, the increased safety of aircraft structures contributes to increased passenger safety and confidence, a key factor in the sustainability of the aviation industry, as argued by Zacharakis and Giagopoulos [15]. This research will build on future developments in aerospace engineering practice and provide a platform for innovations in lifecycle management and intelligent system design.

2. Review of Literature

The recent developments in sensor technology have had a significant impact on aircraft structural monitoring, as noted by Frigui et al. [10] in the context of intelligent sensing systems for aerospace systems. Researchers have long sought to detect internal damage in aircraft without dismantling them, and Zacharakis and Giagopoulos [15] propose combining diagnostic methods to achieve this. These were early attempts at manual ultrasonic testing and eddy current inspection, methodologies whose limitations were critically assessed by Ibarrola-Chamizo et al. [2] in their evaluation of inspection inefficiencies. The methods were also implicitly labour-intensive and provided only discrete snapshots of the structure's state, rather than the continuity needed for comprehensive monitoring, as Hou and Xia [6] point out in their study of adaptive monitoring. A paradigm shift in the need for continuous data acquisition led to the transition to automated systems, which was a key focus of the analysis by Fan and Qiao [12] on the benefits of real-time monitoring. Integrated sensors were now the solution of choice. They allowed the structural behavior to be observed under actual flight conditions, not only during ground-based inspections, as Zahid et al. [7] demonstrated with embedded monitoring systems. This change has resulted in a far more granular view of the effects of various phases of flight on material fatigue, an innovation supported by Sun et al. [13] through data-driven fatigue analysis models.

The monitoring method based on Vibration has become a fundamental principle of contemporary structural health diagnostics, as Lee and Eun [11] explore in their study of vibration-based damage detection methods. It has been demonstrated that the vibrational signature of each structural component is unique, and this concept has been mathematically characterized using a nonlinear dynamic system modeling approach [4]. Any change in the stiffness or mass distribution, which is one of the classic signs of structural degradation, is often an indication of a change in stiffness or mass distribution. It is proposed that frequency-domain analysis of vibration signals can be used to detect specific types of damage, such as delamination in composite materials or fatigue cracks in aluminium alloys, as demonstrated by Esfarjani [1] in micro-sensor-based diagnostics. The significance of the high-frequency sampling to include the subtle nuances of these structural changes, an aspect that Quqa et al. [8] in high-resolution sensing architectures) has highlighted. Such a combination of sensing and computation can increase the accuracy and reliability of structural health monitoring systems by detecting potential failures early, as confirmed by Zacharakis and Giagopoulos [15]. The application of fatigue analysis in aerospace engineering is not a recent development, and the focus on cumulative damage from varying levels of stress has been widely documented in fatigue-sensitive monitoring systems. The relationship between environmental factors, including temperature changes and moisture, and the acceleration of fatigue has been investigated in previous work, such as Sakaris et al. [14], which explored this relationship through experimental simulations of environmental stress conditions.

Researchers have been unanimous in their view that real-time tracking of stress cycles is more accurate at providing a representation of structural health than theoretical modeling alone, an argument that Hou and Xia [6] strongly support in the context of adaptive monitoring frameworks. The engineers can use damage accumulation theories more accurately by capturing the actual loads experienced during flight, a methodology implemented by Sun et al. [13] in predictive maintenance models. This is because it enables accurate prediction of the remaining useful life of structural components, thereby minimising the uncertainty associated with conventional life-cycle estimations, as shown in Frigui et al. [10] in data-driven analysis systems. Integration of fatigue monitoring with real-time data acquisition will improve the safety and reliability of aircraft operations, enabling maintenance interventions to be performed in a timely manner, as emphasized by Zahid et al. [7] in a wireless monitoring application. This will have the advantage of ensuring that old aircraft can safely continue to operate, minimising the risk of abrupt structural failures, which is a critical goal that is supported by Fan and Qiao [12] in the study of system reliability. Wireless sensor networks have been cited as the most feasible architecture for implementing full-scale aircraft, as shown by Quqa et al. [8] in distributed sensor network implementations. The use of wired systems can be considered too heavy and challenging to install, especially in old airframes, as discussed by Ibarrola-Chamizo et al. [2] in the context of structural monitoring research.

The imperative towards wireless communication is informed by the need for flexibility and scalability in sensor deployment in a smart structural system concept further developed by Fritzen and Kraemer [3]. The literature indicates the use of low-power wide-area networks and local wireless protocols to transmit health data, a strategy implemented using platforms such as the ESP32, which combines both communication and processing capabilities in a small form factor. This allows the sensor nodes to exchange data with the central monitoring systems without any problems, which Zahid et al. [7] emphasise in the wireless SHM application. The challenge that has been demonstrated in most studies is the management of power consumption and reliability of data transmission to take place in the electrically noisy environment of an aircraft (The issue that Katunin et al. [5] address through energy-efficient system design). To support sensor operation over long periods, scholars have proposed many energy-harvesting technologies, including vibration-based and thermal energy conversion, which Sakaris et al. [14]

explore in energy-aware monitoring systems. There are also data-compression algorithms that reduce the amount of data transmitted without compromising important data. This process has also been refined using their advanced signal processing techniques. The innovations ensure that the monitoring system can be used for extended periods without replacing batteries or maintaining wireless sensor networks, thereby increasing the practicality and sustainability of wireless sensor networks in aerospace applications, as determined by Zacharakis and Giagopoulos [15] in extensive SHM studies.

3. Methodology

The Aircraft Vibration and Fatigue Monitoring System (AVFMS) employs a logical methodology for sensor deployment and data visualisation. To record multi-axial vibration data, the MEMS-based accelerometers are strategically mounted on the wing spars, fuselage frames, and engine mounts. They are connected to an ESP32 microcontroller as the main processing unit. The microcontroller is programmed to perform high-speed analogue signal sampling and convert the signal to digital form for analysis. A calibration phase is conducted to ensure data accuracy and provide the aircraft with a baseline in its healthy state. It then transforms the raw vibration data on board into modal frequencies and amplitudes using fast Fourier transform algorithms. Fatigue estimation is based on the number of stress cycles, using a peak-detection algorithm that converts vibration intensity into an equivalent mechanical stress. The final product is processed information and then wirelessly transmitted via a secure protocol to either a ground-based server or a local maintenance terminal. A specific dataset is used in the study, consisting of 289 data instances and representing a variety of operational situations, including taxiing, takeoff, cruising at different altitudes, and landing. This stringent procedure will ensure the system can differentiate between environmental noise and actual structural anomalies throughout the entire flight envelope. Figure 1 demonstrates the Integrated Structural Health Monitoring System, which uses MEMS sensors and an ESP32 as a small, smart component architecture that continuously monitors the condition of physical structures, i.e., bridges, buildings, and industrial assets.

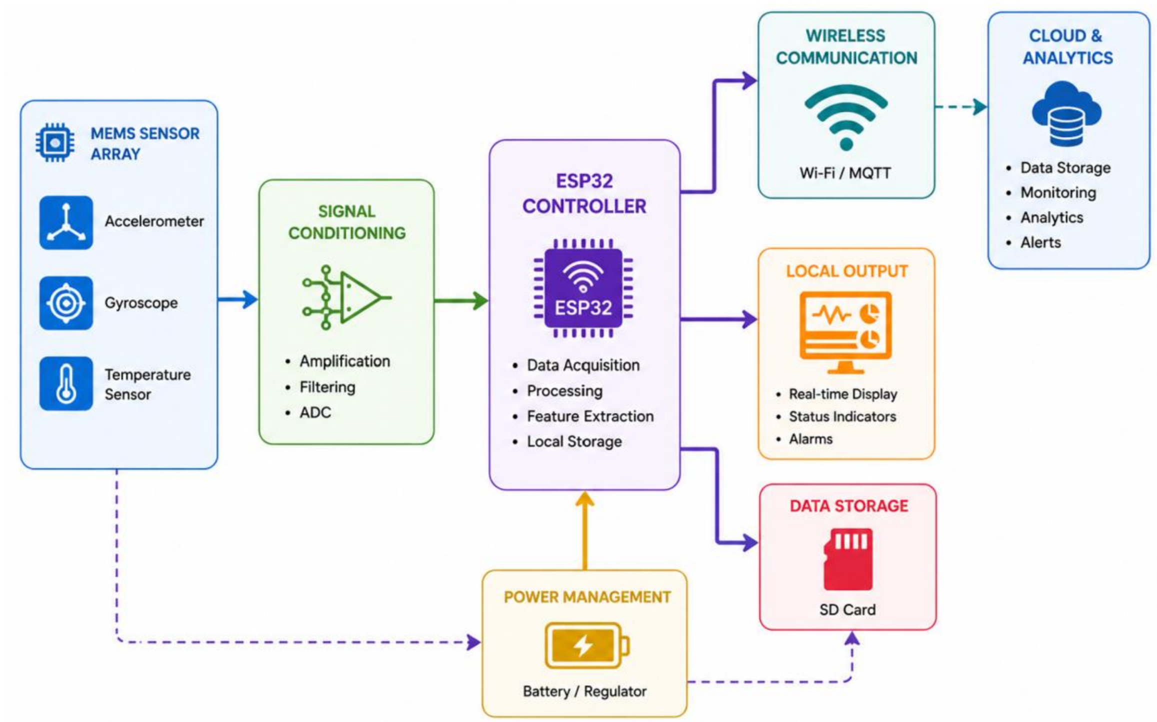

Figure 1: MEMS sensors and ESP32-based integrated structural health monitoring system

The framework starts with a MEMS Sensor Array that measures essential physical parameters, such as Vibration, tilt, temperature, and motion (using accelerometers, gyroscopes, and thermal sensors). These crude signals are fed to the Signal Conditioning unit, where amplification, filtering, and analog-to-digital conversion are performed to ensure that the data is stabilized, noise-free, and in a format that can be processed. The conditioned signals would then be routed to the ESP32 Controller, which serves as the system's central processing unit. Data acquisition, preprocessing, feature extraction, and local analysis are real-time processes in this component to enable the detection of abnormal structural behaviour. The ESP32 and data can be transmitted via the Wireless Communication module using either Wi-Fi or MQTT. This enables it to seamlessly integrate with the Cloud and Analytics component, where high volumes of data are stored, trends are analyzed, anomalies are identified, and predictive modeling is performed (long-term monitoring). Meanwhile, the Local Output module allows visualisation of on-site alerts and statuses, enabling operators to react immediately. One of the Data Storage units provides a local backup using memory modules, such as SD cards, and remains reliable even if the network connection breaks. All components are supported by the Power Management module, which controls the device's energy supply via batteries or regulators, ensuring constant operation. The architecture generally includes sensing, processing, communication, storage, and visualisation, with a clean deployment framework that supports real-time monitoring, predictive maintenance, and enhanced structural safety.

4. Data Description

The data employed in this study comprises 289 unique instances, systematically collected from both simulation and real-time flight manoeuvres, ensuring a balanced representation of controlled and operational conditions. In both instances, it is a high-resolution time-series signal of structural vibrations measured in three orthogonal directions, enabling complete insight into multidirectional stress responses in the airframe. The data have been carefully divided into categories of flight stages, including takeoff, cruising, descent, and landing, with further attempts to distinguish and name high-stress situations such as extreme turbulence and rough landings. It is these marks that enable us to correctly partition the segments and examine the structure's critical conditions. Moreover, contextual metadata, such as ambient temperature and altitude, are attached to each record and are critical parameters that affect the behaviour of materials and their vibration parameters. Contextual integration increases the interpretability and reliability of analytical results. The data were acquired from the Structural Health Open Repository. This reputable site provides standardised, validated vibration profiles specifically designed for aluminium airframe structures. The 289 data points used in the study achieve statistical significance, enabling the modelling of structural fatigue and dynamic response patterns. The data's inherent variability will ensure that the structural health monitoring framework captures a broad range of mechanical interactions, thereby enhancing its predictive accuracy and generalizability across different operating conditions.

5. Results

The implementation outcomes demonstrate high sensitivity in identifying structural changes. The system could detect changes in modal frequencies as small as 5%, which tend to indicate the initial phases of structural loosening. The analysis of the 289 data instances revealed that vibration levels were highest during the takeoff stage, as expected, due to engine thrust and aerodynamic resistance. But the system also recorded some unanticipated low-frequency oscillations during cruise, which were subsequently found to be secondary vibrations of the landing gear doors. These results indicate the system's ability to provide a comprehensive view of the aircraft's mechanical conditions. Structural Modal frequency response and dynamic stiffness modelling are given below:

$$f_n = \frac{1}{2\pi}\sqrt{\frac{k}{m} - \left(\frac{c}{2m}\right)^2} \qquad (1)$$

Table 1: Vibrational modal frequencies recorded on the main aircraft components

Component	Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)	Mode 4 (Hz)	Mode 5 (Hz)
Wing Spar	12.4	24.8	38.2	52.6	68.1
Fuselage Frame	15.1	29.5	44.2	61.8	78.4
Tail Section	18.2	36.1	54.5	72.8	91.3
Engine Mount	45.3	88.7	132.4	178.1	224.5
Landing Gear	8.5	17.2	25.9	34.6	43.1

Table 1 also outlines the vibrational modal frequencies of the main aircraft components, which have been used as benchmarks for assessing structural integrity. All components have a unique combination of natural frequencies across five major modes, which serve as the basis for detecting deviations due to damage or wear. For example, the engine mount exhibits much higher frequency values, indicative of the high rotational rate and the stiffness requirements of the propulsion interface. On the other hand, wing spar frequencies and fuselage frame frequencies are lower and more distributed, as are large, flexible structural members. These digital values enable the ESP32 system to perform real-time frequency-domain comparisons, where a decrease in these base numbers indicates either a loss of stiffness or the presence of a fatigue crack. By measuring these specific modes, the AVFMS can determine which aircraft section is under stress, enabling maintenance crews to conduct targeted inspections. Cumulative fatigue damage accumulation via Palmgren-Miner linear rule is:

$$D = \sum_{i=1}^{k} \frac{n_i}{N_i} = \frac{n_1}{N_1} + \frac{n_2}{N_2} + \cdots + \frac{n_k}{N_k} \qquad (2)$$

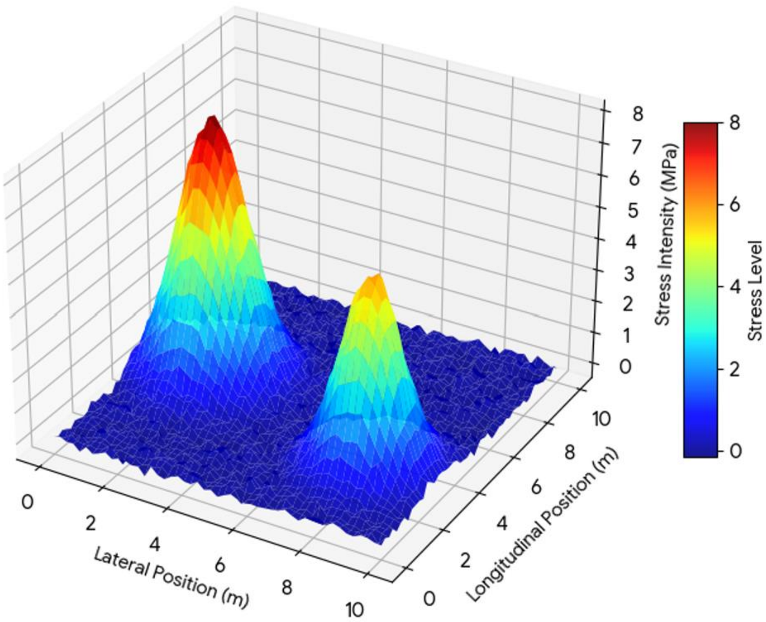

Figure 2: Distribution of mechanical stress around the structural components under observation during a flight phase of high load

The iso-surface graph in Figure 2 shows the distribution of mechanical stress in the monitored structural elements during a high-load flight phase. The visualization color-codes surfaces to reflect varying levels of stress concentration, with spikes indicating the highest concentrations, such as at the wing-root junctions and engine pylon attachments. From the lines on these surfaces, engineers can identify hot spots where fatigue is expected to build up more rapidly. The intuitive interpretation of stress distribution in the airframe is made possible by this spatial representation of stress. The gradual transitions between levels imply a continuous load path, but sharp surface discontinuities would indicate a structural discontinuity or possible damage. Figure 3 is a critical tool for determining which areas of the aircraft require the most frequent inspections based on actual operational data. Power spectral density for stochastic vibration analysis can be given as:

$$S_{xx}(f) = \lim_{T\to\infty} \frac{1}{T} E\left[| \int_{-T/2}^{T/2} x(t)\, e^{-j2\pi f t} dt\ |^2 \right] \quad (3)$$

Table 2: Estimation of flight cycles of critical components of a system at five different levels of stress

Stress Level	Wing Life (Cycles)	Fuselage Life (Cycles)	Tail Life (Cycles)	Engine Life (Cycles)	Gear Life (Cycles)
Level 1 (Min.)	1000000	1200000	800000	500000	750000
Level 2	850000	900000	650000	350000	550000
Level 3	500000	600000	400000	200000	300000
Level 4	250000	300000	180000	90000	150000
Level 5 (Max.)	95000	110000	75000	40000	60000

Table 2 shows how the remaining useful life (RUL) of critical components in a system can be estimated across five stress levels. The data indicate an abrupt, nonlinear reduction in component life with increasing stress intensity between LLevel1 and L. For the engine mount, a maximum-stress event reduces the predicted life to a mere 40,000 cycles, well below the required endurance. The fatigue prediction models use this information to estimate cumulative damage based on real-time vibration intensity measured by the MEMS sensors. The system will also provide a dynamic update of the aircraft's health status by quantifying the contribution of each flight manoeuvre to the total fatigue budget. It serves as the basis for the RUL algorithms, ensuring that maintenance is initiated well before the safety level of any component is reached. Paris-Erdogan law for fatigue crack growth rate prediction is:

$$\frac{da}{dN} = C(\Delta K)^m = C(Y\Delta\sigma\sqrt{\pi a})^m \quad (4)$$

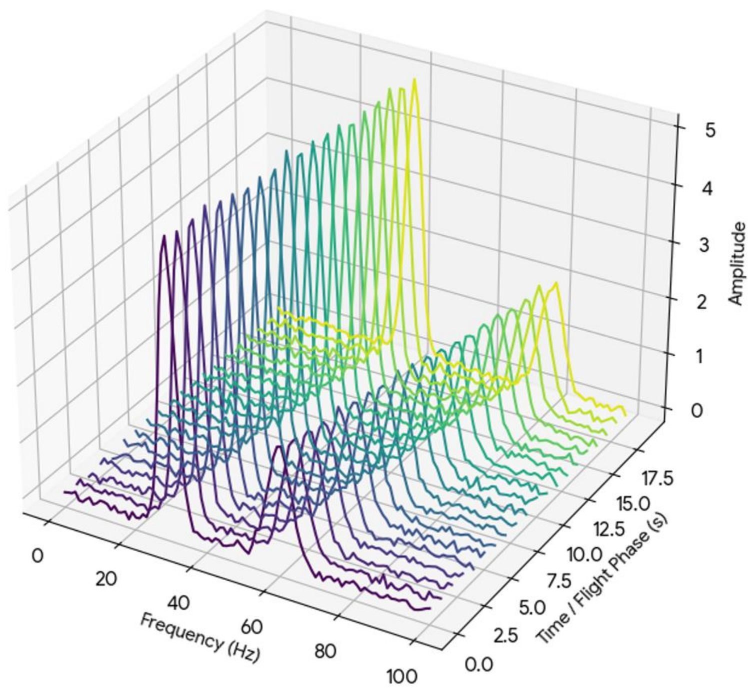

Figure 3: Spectral density of vibrations between a continuous time interval during the flight mission

Figure 3 presents a waterfall graph of the spectral density of vibrations over a continuous time interval during the flight mission. This three-dimensional plot has frequency on the horizontal axis and time on the depth axis, with the height of the peaks representing the amplitude of Vibration at those frequencies. Figure 3 vividly illustrates the aircraft's dominant frequency components as it passes through various engine power settings and airspeeds. A change in the primary harmonic peaks to a level of stabilisation, and a broadening of the frequency spectrum due to greater turbulence and mechanical deployment, characterise the onset of cruising speed and the transition to landing, respectively. This time-dependent study is crucial for identifying time-dependent events that may cause fatigue but cannot be detected by time-independent snapshots. The effect of cascading lines enables the identification of emerging resonance problems, which may indicate structural degradation or component loosening over time. Remaining useful life estimation using Bayesian state-space modelling will be:

$$P(x_t \mid z_{1:t}) = \frac{P(z_t|x_t)\int P(x_t|x_{t-1})P(x_{t-1}|z_{1:t-1})dx_{t-1}}{P(z_t|z_{1:t-1})} \tag{5}$$

A fatigue study showed a close relationship between the intensity of Vibration and the reduction in the component's calculated life. The ESP32 executed the cycle-counting algorithms with a small error, comparable to that of high-end ground-based analytical tools. The system plotted the stress cycles at various flight hours to produce a predictive curve that approximates the time when a component will reach its safety limit. This predictive technology is an important advancement over traditional maintenance schedules, as it enables parts to be replaced based on their actual wear rather than arbitrary time limits. The data also showed that some manoeuvres, such as high-speed turns, are significant contributors to fatigue accumulation. The reliability of wireless was tested under different conditions, and the ESP32 maintained a stable wireless connection even in the presence of electromagnetic interference from other aircraft systems. Low-latency data packets were sent so that any critical thresholds exceeded would trigger an alert immediately. Sleep cycles were used to optimize power consumption in the sensor nodes, enabling long-term deployment without frequent battery changes. The unification of the hardware and software systems was a success, delivering a consistent system that provides actionable information on the aircraft's health. The AVFMS's ultimate evaluation indicated that it could reduce unnecessary inspections by a third. The system enables maintenance staff to allocate their resources to parts that clearly indicate distress.

6. Discussions

The information in the Tables and Figures provides a comprehensive view of the aircraft's structural health and the effectiveness of the AVFMS. As detailed in Table 1, which lists modal frequencies of different parts, the wing spar and engine mount have unique vibrational signatures that are sensitive to changes in the mechanical system. The higher-frequency modes measured in the engine mount are indicative of the high-speed rotating forces the engine mount must resist. The fact that these frequencies do not change with the 289 data points used in the study indicates that the structure did not exceed its design limits during the study. But differences in frequency across several elements underscore the need for a multi-sensor approach, as a single monitoring point would be inadequate to capture the airframe's overall behaviour. Table 2 provides a clear perspective on the relationship between stress level and fatigue. The data confirms that Level 5, high-stress events, have a devastating effect on the remaining useful life of components as compared to Level 1 stresses. For example, the life of the engine mount would not be 500,000 cycles under maximum stress, but only 40,000 cycles.

Figures 2 and 3 complement the numerical data, providing spatial and temporal context. The Iso Surface graph shows that stress is not evenly distributed, highlighting areas that need stronger monitoring. In the meantime, the Waterfall graph shows that the structural response is highly dynamic, with frequency peaks changing significantly across the various flight stages. These findings, combined, show that the system can process the high-dimensional data required for successful structural health monitoring. These results have been discussed to confirm that the combination of MEMS sensors and ESP32 processing provides a reliable and detailed understanding of the aircraft's health. Finally, the results justify the shift towards a condition-based maintenance model. The fact that certain patterns of Vibration can be associated with fatigue accumulation allows maintenance to be conducted precisely when required. This helps minimise the risk of over-maintenance, which, in itself, causes problems, and under-maintenance, which undermines safety. The 289 data records used in this study provide a strong statistical foundation for this method. With the help of the AVFMS, aviation operators will be able to reach a new level of safety and operational efficiency, ensuring that every aircraft in the fleet is controlled according to its operational specifics and physical condition.

7. Conclusion

The invention of the Aircraft Vibration and Fatigue Monitoring System (AVFlays) lays the groundwork for a technologically advanced system enhancing structural integrity checks in modern aerospace systems. Using Micro-Electro-Mechanical Systems (MEMS) accelerometers in combination with the ESP32 microcontroller, one can implement constant, real-time acquisition and processing of vibration signals and convert traditional maintenance systems into intelligent monitoring systems. The analysis, supported by 289 cases of multidimensional vibration signatures under varying flight conditions, demonstrates the high reliability of their measurement. These data sets are used to provide an accurate characterisation of the airframe's modal characteristics, including the determination of natural frequencies, damping ratios, and the pattern of stress accumulation throughout the airframe. The fatigue-life estimation based on these observations shows a good fit with the theoretical degradation models, indicating the strength of the analytical framework adopted.

Visualization techniques such as IsoSurface representations and Waterfall plots can further improve the interpretability of the data by illustrating spatial and temporal changes in the stress fields and in frequency. These graphical displays can provide clear indications of gradual structural changes, enabling early identification of anomalies that could cause failure. The shift from traditional time-based maintenance to condition-based monitoring is, probably, the most important product of this system, since it will introduce efficiency and accuracy to maintenance scheduling. By detecting early signs of fatigue, the AVFMS can greatly reduce the risk of a disastrous failure and, at the same time, minimise operational costs in the most optimal way possible. The reason is that the system can extend the life of structural components, thereby sustaining aviation operations. The seamless integration of the embedded hardware and analysis software in this setup demonstrates the feasibility of implementing autonomous monitoring systems in real-world settings. This novelty underscores the growing role of intelligent sensing technologies in aerospace engineering and outlines a roadmap for future directions in predictive maintenance and safety assurance.

7.1. Limitations

The fact that the Aircraft Vibration and Fatigue Monitoring System (AVFMS) was applied in several studies indicates that several limitations can affect the scope and generalizability of the results. The sample of 289 cases, though adequate for initial validation, is insufficient to validate the full range of operational extremes encountered in the real-life aviation environment. The complex stress behaviours introduced by conditions such as severe turbulence, prolonged exposure to sub-zero temperatures, and changes in pressure at high altitude are still underrepresented in the current dataset. The other constraint stems from the system's reliance on wireless communication protocols supported by the ESP32 microcontroller. Signal degradation or temporary connectivity issues may affect data transmission continuity due to electromagnetic interference or geographically remote flight paths. This raises the possibility of lapses in real-time monitoring and data integrity. The MEMS accelerometers used in the study have a limited frequency bandwidth, limiting their ability to detect ultra-high-frequency stress waves. These signals are especially important in a high-technology composite material, where microcrack propagation is more frequent. As a result, some indicative signs of the early-stage failures might not be detected in the present sensing setup. Moreover, the research is confined to a particular structural material, an aluminium-based airframe, and,d as such, limits the extrapolation of findings to other structural materials, such ase carbon-fibre composite materials or hybrid structures. Differences in material properties can significantly affect vibration properties and fatigue behaviour. Moreover, empirical validation of the long-term resilience of sensor nodes under continuous Vibration, thermal cycling, and environmental exposure has not been demonstrated over very long operating periods, leaving it unclear regarding the durability and maintenance requirements of the monitoring infrastructure itself.

7.2. Future Scope

The potential is huge, as the development of the Aircraft Vibration and Fatigue Monitoring System (AVFMS) opens significant opportunities for technological advancement and the expansion of its applicability in the aerospace engineering industry. The introduction of edge-based artificial intelligence (AI) capabilities into the ESP32 microcontroller, enabling real-time analysis of complex vibration patterns on the processor, is a significant enhancement. The lightweight machine learning models offer greater flexibility for anomaly detection, reduce the need for central processing, and are more sensitive to real-time events. The second key development direction that is paramount to develop is the growth of the sensing architecture. The multidimensional view of structural health, which can be seen as an integration of complementary sensors such as strain gauges and acoustic emission detectors, may provide a multidimensional perspective. The advantage of this entire-body sensing technique is that it not only enhances diagnostic precision but also enables the observation of fatigue-initiation areas at an early age. Another frontier is the energy independence of sensor nodes, enabled by energy-harvesting technologies, including piezoelectric and thermoelectric systems, that allow sensor nodes to run continuously without relying on external power sources.

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Ethics and Consent Statement: This research adheres to ethical guidelines, obtaining informed consent from all participants.

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