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Real Time Platform for Monitoring Durability Testing of Aircraft Landing Gear

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Abstract. This paper presents an endurance post-processing platform for monitoring durability and resistance testing of aeronautical mechanical and hydraulic systems, focusing on aircraft landing gear. The platform integrates data acquisition and monitoring to ensure consistency and compliance of the bench test and components under examination. Automated MATLAB® scripts capture critical parameters such as operational pressure, return pressure, extension and retraction line pressures, door load, aerodynamic drag load, landing gear angle, and temperatures of hydraulic lines and ambient conditions. Descriptive statistical analyses, including histograms and box plots, are conducted to provide a deep understanding of the laboratory tests and determine the percentage of the test cycle within predefined acceptable limits. Multivariate analysis discerns correlations between test parameters, aiding in the development of machine learning algorithms for classifying and/or predicting anomalous behaviors. It is shown that the integration of real-time monitoring, detailed statistical analysis, and machine learning enhance test accuracy and reliability. The preliminary results indicate that this methodology optimizes testing processes, reduces diagnostic time, and lowers costs by proactively identifying potential issues early. It is understood that the current research can contribute significantly to improving the reliability, maintainability, and availability (RMA) of aeronautical systems, aligning with the standards of scientific literature in mathematical, computational, mechanical, and aeronautical engineering.

Keywords: Machine Learning, Test Optimization, Landing Gear, Durability, Multivariate Analysis.

1 Introduction

The aircraft landing gear and its associated systems represent a compelling design challenge: the retractable landing gear is simultaneously system, structure, and machine; it supports the aircraft on the ground, absorbs landing and braking energy, permits maneuvering, and retracts to minimize aircraft drag. The landing gear is one of the most complex and diverse systems on an aircraft. An article on the Flight magazine in 1940, quoted by Currey (1988), expressed this as “for on no other part of the aeroplane is there such scope for engineering ingenuity and no other part can boast of so many ways of achieving the desired result”. This remains true today, many decades later.

An expert in landing gear must be conversant with a wide range of engineering disciplines including materials, mechanisms, structures, heat transfer, aerodynamics, tribology, and many more. Depending on the given aircraft’s needs, a landing system may be little more than wheels and tires attached to suitable aircraft structure or it may be

a complicated system enabling performance on unpaved runways, steering, kneeling, retracting, and permitting further aircraft operations.

Performance testing of aeronautical systems inherently requires extensive interdisciplinary integration, demanding the application of advanced engineering analyses across multiple domains of expertise to establish rigorous acceptance criteria for system behavior. To ensure the reliability of each evaluation, the test rig is comprehensively instrumented with high-precision transducers, enabling accurate acquisition of relevant physical parameters throughout all the testing phases. Consequently, both the availability of measured data and the associated computational records must be systematically organized and transparently presented to certification authorities in a manner that is technically robust and auditable.

From an operational perspective, the platform developed in this study addresses three fundamental requirements: (i) structured management of data acquisition processes, (ii) verification of test acceptance through statistically validated methodologies, and (iii) generation of auditable and traceable technical documentation.

From a strategic perspective, the outcomes of this work directly support the design, qualification, and validation processes of the landing gear system. The proposed tool contributes to the mitigation of qualification errors, provides quantitative demonstration of compliance with engineering and certification requirements, and enhances the reliability of endurance testing by enabling anticipatory prognosis of system performance. Figure 1 presents a schematic overview of the system under investigation.

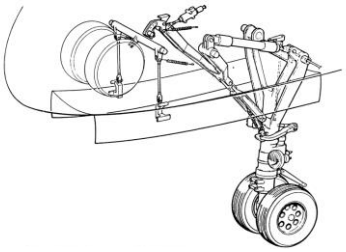


Figure 1: Nose landing gear subsystem Architecture. (Source: Roskam, 1989).

The Nose Landing Gear (NLG) serves as a load-bearing and shock-attenuating assembly that transfers dynamic and static ground loads—arising from landing, taxi, and ground handling—through the axle interface to the primary airframe structure. In addition to its structural and damping functions, the NLG provides directional control during ground maneuvering operations, as Schmidt (2022) describes.

Retraction and extension of the NLG are hydraulically actuated. The NLG Retract Actuator initiates gear retraction and deployment, while the Unlocking Actuator enables disengagement of the mechanical downlock prior to gear stowage. In the extended (down-and-locked) position, positive mechanical locking is achieved via the drag strut, locking stay, and downlock spring, which work in conjunction with the unlocking actuator. When fully retracted, uplock security is maintained by the Uplock Box assembly, which prevents uncommand gear extension due to airframe vibration or hydraulic fluctuation. Figure 2 indicates the basic components of NLG assembly.

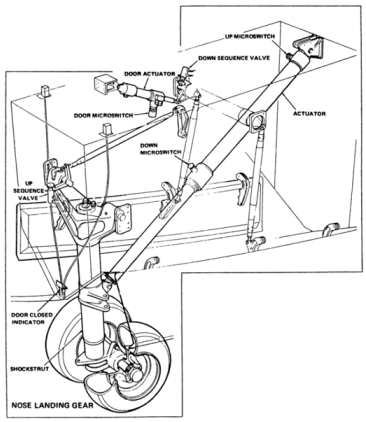


Figure 2: NLG subsystem. (Source: Roskam, 1989).

2 Methodology

2.1 Endurance Test

The Endurance Test Procedure defines the qualification methodology for evaluating the operational durability of the Nose Landing Gear (NLG) subsystem, encompassing cyclic actuation (retraction and extension), steering functionality, and shock absorber performance throughout the design service life. The test campaign is structured in accordance with the applicable system-level requirements outlined in the approved technical specifications, and aligns with the endurance and reliability criteria stipulated under Federal Aviation Administration (FAA) Part 25 certification guidance for retractable landing gear systems. Although developed to satisfy FAA compliance, the procedure is also harmonized with corresponding European Union Aviation Safety Agency (EASA) CS-25 and Agência Nacional de Aviação Civil (ANAC) RBAC 25 standards, ensuring conformity across multiple regulatory authorities. The qualification sequence is intended to validate subsystem robustness under representative load spectra, environmental factors, and operational cycles consistent with the aircraft's intended usage profile.

The qualification test program for the NLG subsystem is designed to simulate a comprehensive range of operational conditions representing the gear's expected service life. The test encompasses normal retraction and extension cycles equivalent to full-life flight operation, maintenance-related actuation cycles reflecting scheduled ground servicing events, and emergency extension scenarios under non-nominal conditions, including loss of system pressure.

Testing is conducted across a defined thermal envelope, including low temperature (cold soak), ambient, and high-temperature conditions, to ensure functional integrity under varying environmental stresses. Lubrication and inspection tasks are carried out in accordance with the procedures outlined in the Component Maintenance Manual (CMM), ensuring that maintenance activities are realistically represented throughout the test campaign. Each setup described is established on the testing rig, Figure 3 shows.

Hydraulic cycling is performed using fluid conforming to the particulate contamination levels specified in SAE AS4059, maintaining system cleanliness in accordance with standard aerospace hydraulic requirements. The test procedure is structured to represent retraction and extension cycling through the total number of life-designated actuation events. Aerodynamic and drag loads are applied to the test article via a calibrated rig, simulating the mechanical and structural loads experienced during flight and ground operations.

Operational load cases include normal retraction, normal extension, and emergency extension scenarios, ensuring the system's ability to perform reliably across all the expected use cases. Throughout these cycles, the angular displacement of the retraction and extension mechanisms is monitored and validated against the maximum allowable kinematic envelope, confirming compliance with the design tolerances and verifying proper gear deployment and stowage under all tested conditions.



Figure 3: Testing rig overview. (Source: Roloff, 2002)

2.2 Acquired Data

The endurance test initial setup phase involves preparing the equipment and test samples. It includes calibrating instruments, installing sensors, and configuring the test apparatus according to the specific requirements of the endurance test. Thereafter, the test samples are subjected to repeated cycles of stress or load to simulate real-world

operating conditions. This could involve mechanical, thermal, or hydraulic cycling, depending on the nature of the test and the component being evaluated.
After the cycling phase, the test setup is disassembled to inspect the test samples. This step involves carefully taking apart the equipment and components to examine them for any signs of wear, damage, or failure. The data collected during the cycling phase is exported for analysis. This includes measurements of relevant parameters indicated on the Table 1. The data is transferred to an acquisition software for signal processing and then to endurance platform postprocess for further processing and evaluation.

The test setup is reconfigured for the next phase or to a different test scenario. This involves adjusting the setup parameters, changing test samples, and preparing for the next round of endurance testing. The cycle then repeats from the setup phase. This process ensures a systematic approach to evaluating the durability and performance of components under various conditions, providing valuable data for improving design and reliability.

Table 1. Acquired Data

Pressure	Temperature	Load	Others
Operational	Room	Aerodynamic Door	Time
Return	Down Lock	Aerodynamic Drag	Number of Total Cycles
Retraction	Up Lock Box		Landing Gear Angle
Extension	Actuator		Proximity Up Lock Box sensor
	Operational Fluid		Proximity Lock Stay sensor
	Return Fluid		
	Extension Line Fluid		
	Retraction Line Fluid		

For this study, an Exploratory Data Analysis (EDA) was applied to calculate various statistical variables to better understand the distribution and relationship among acquired data. The results obtained from the endurance test were also processed using a developed post-processing tool, enabling analysis at four distinct levels.

Initially, the post-processing platform facilitated the monitoring of the ongoing test to ensure its compliance with the required parameters, demonstrating the repeatability and behavior of both the test rig and the component under analysis. Upon finishing the monitored test, the post-processing provided an analytical basis for the systems engineering team to evaluate system compliance and offer a prognosis on the corresponding performance, approving or disapproving the component based on the expected functional aspects.

At a third stage, also conducted on the developed platform, the EDA showcased the variability of the acquired parameters through statistical metrics. This included histograms, box-plots, descriptive statistical analysis, parameter correlation, and graphical analysis to illustrate how the signals acquired by the transducers behaved, allowing for inferences on the system's stability. This analysis determined the best-fit statistical density distribution for the variables and calculated the probability that the observed behavior remained within the specified limits. These calculations are direct indicators of the system's demonstrated reliability.

Finally, the post-processing platform provided analytical, mathematical, and computational content to support a developing machine learning architecture. The pertinent results are presented and discussed below.

3 Results

3.1 Test Monitoring

The monitoring interface for the test transducers presented so far enables graphical visualization of the test in curves as a function of time and the angular position of the landing gear, allowing for visual verification of limits and comparison between different cycles. However, this visualization is subjective regarding the dispersion of the monitored parameters. Monitoring the maximum and minimum limits ensures compliance with the parameters established in the test procedure, but it does not show whether the measurement dispersion exhibits precision, accuracy, trends, and errors that, beyond the limits, provide information on the stability of the system's behavior under test.

To address this issue, each acquired parameter was subjected to descriptive statistical calculations, enabling the construction of histograms, box plots, and correlations. Figure 4 presents several histograms created with blocks of data acquired during low-temperature test setup. The histogram ensures an understanding of the frequency at which certain values occur relative to others, which can be useful for identifying how often outlier values occur.

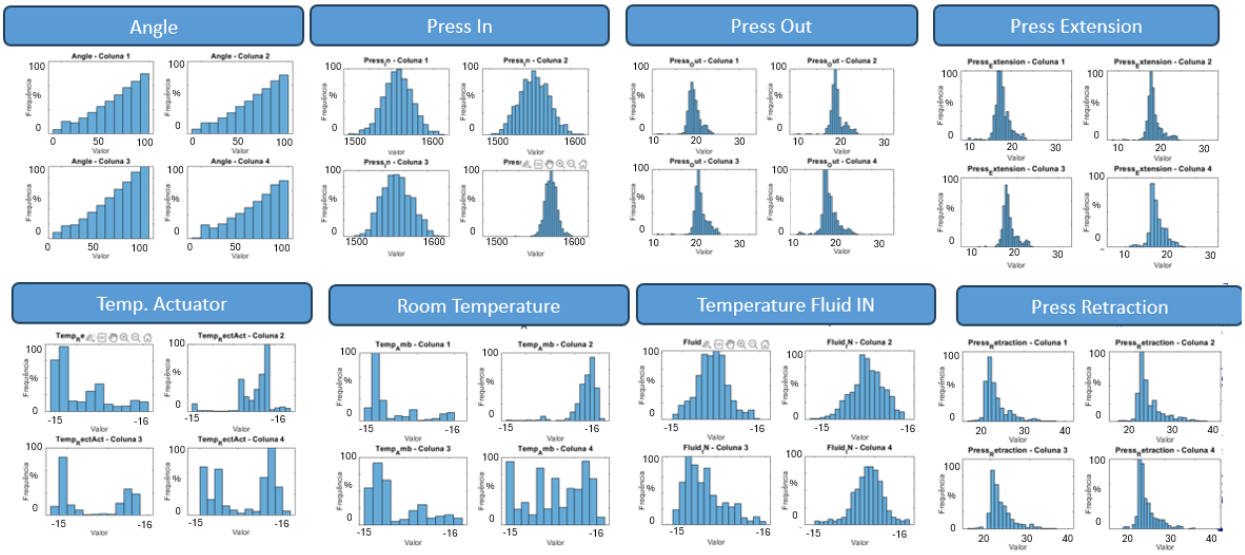


Figure 4: Histograms - low temperature setup.

Alongside the histogram, a boxplot for each acquired variable was created, allowing for monitoring how the mean, maximum, and minimum values, as well as discrepancies (outliers), behaved throughout the test. Figure 5 presents the boxplot created for the test with a normal temperature setup, in which the full life cycles of extension and retraction of the landing gear were performed. It also shows how the visualization of the behavior of all cycles is facilitated, and conclusions about anomalies are immediately perceptible. By processing all data points acquired during the test, the boxplot provides information on the entire static and dynamic behavior of the system, enabling the correlation of the boxplot variability with potential non-conformities in the test or the component under evaluation.

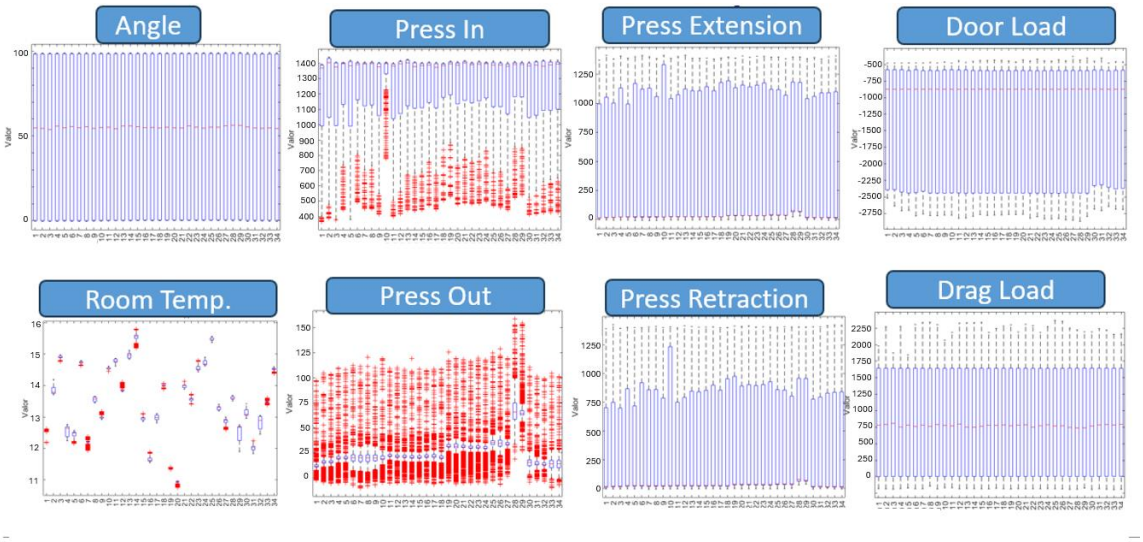


Figure 5: Box Plots - Normal condition.

Principal Component Analysis (PCA), also known as discrete Karhunen-Loève transform (KLT), Hotelling transform or proper orthogonal decomposition (POD), allows for the conversion of a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components, according Navidi (2014). This mathematical procedure should be refined alongside the developing machine learning framework, but initially it already enables the monitoring of the correlation between variables, which can provide information not available when the acquisitions are evaluated in isolation.

Figure 6 presents the correlations between different variables for the performed test with a normal temperature setup. It is possible to graphically classify whether the variables behaved similarly from one cycle to another. If there is variation, investigations should be conducted.

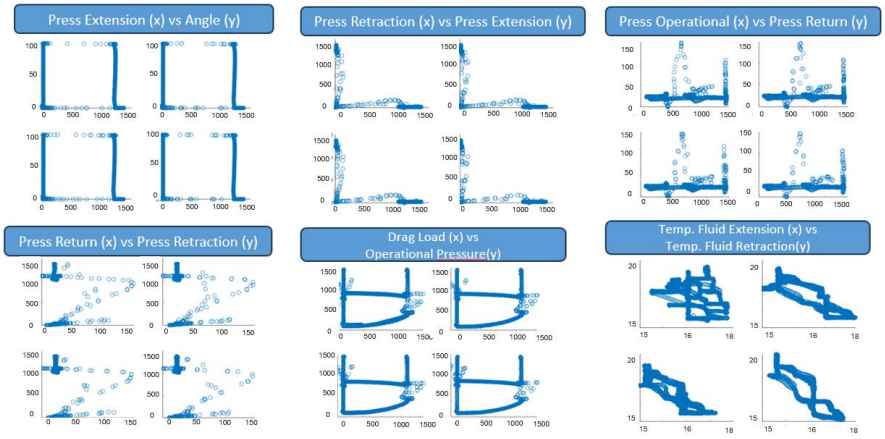


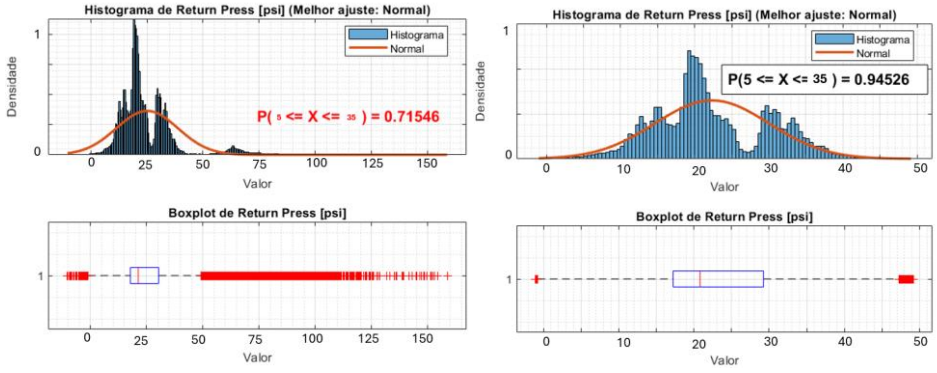
Figure 6: Correlations - Normal condition setup.

3.2 Exploratory Data Analysis

The analyses so far have been dedicated to observing test compliance. However, the data processing was also conducted to gather information about the reliability of the component and the test system. For this purpose, the developed analyses were used and further refined with exploratory statistical studies.

3.2.1 Return Pressure

By compiling all test cycles into a single block, a histogram for the entire test was created, and different statistical distributions were tested to identify the best representation for the variable, with the normal distribution being the most appropriate. Figure 7(a) shows that the probability of the return pressure throughout the test being within the limits established by the procedure is 71.55%.
However, analysis of the return pressure line behavior, in conjunction with the constructive characteristics of the hydraulic test rig, revealed that peripheral equipment introduced interference in the transducer signal acquisition. In light of this finding, the elimination of outlier points was deemed technically justified. Accordingly, the engineering assessment established that all data values deviating by more than three standard deviations from the mean value should be excluded from the dataset.
After doing this and recalculating the distribution and probability, the test shows 94.52% compliance within the limits established by the procedure, as shown in Figure 7(b).



(a) (b)

Figure 7: Statistical density distribution (a) with outlier (b) without outliers.

3.2.2 Retraction and Extension Pressure

While the return line pressure exemplifies a variable that carries information about the test rig, the retraction line pressure provides more direct information about the landing gear under test. The graphs and parameters developed were analyzed to seek, in addition to test repeatability, insights into the constructive behaviors of the mechanism that can be related to the measurements. As the retraction line pressure is also influenced by the mechanical behavior of the actuator, where the transducer reads the signal, it is possible to directly infer how the component behaves throughout each test cycle, allowing monitoring of its internal elements during the entire test.
The integration of all blocks into a single entity is performed in this scenario, allowing correlations with different variables. However, at this stage, the focus is on performing constructive diagnostics of the component, rather than mere test repeatability, as depicted in Figure 8(a). The same process applied to the retraction line pressure was performed on the extension line pressure.
When all cycles are compiled into a single block, it is noted how this graph provides information that can be seen in the boxplot. The statistical procedure of building the boxplot reveals evidences that can indicate internal failures of the component without the need for its disassembly. Analyses can then be redone, allowing for an overall understanding of the test behavior rather than an individualized block-by-block view, as shown in Figure 8(b).



(a) (b)

Figure 8: Correlations: (a) Retraction pressures *vs* extension pressure; (b) Extension pressure *vs* angle position

4 Conclusion

The Post-Processing Platform developed for the endurance test allowed the monitoring of test anomalies, diagnosis of root causes of observed non-conformities, failure prediction, and demonstration of the reliability of both the test and the component under analysis. This approach advanced the prognosis that would typically be made only at the end of the test, with acceptance tests and the disassembly of components for visual and dimensional evaluations. In general, the monitored parameters remained stable, which expedited the conclusion of the endurance test, showing no failures, leaks, or excessive wear of the metallic or polymeric mechanical components of the tested landing gear system. This platform provides a robust tool to preemptively mitigate test failures while showing the consistency and reliability of the analyzed system. The quality of individual components and the integrated system is subject to observation, quantification, and qualification, ensuring an evaluation with precise metrics and procedures to guarantee the quality required by the design specifications for aeronautical systems.
This platform continues to gain mathematical and computational maturity and is currently being directed towards the development of machine learning architecture, supported by Anastasiadis (2020) techniques. This architecture will be trained with data from previous tests to classify and predict failures that may occur in the landing gear system.

5 References

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