AIAA SCITECH 2024 Forum, 8-12 January 2024, Orlando, USA. Paper number AIAA 2024-0759
DOI:10.2514/6.2024-0759

Advancing Fault Diagnosis in Aircraft Landing Gear: An innovative two-tier Machine Learning Approach with intelligent sensor data management

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Revolutionizing aircraft safety, this study unveils a pioneering two-tier machine learning model specifically designed for advanced fault diagnosis in aircraft landing gear systems. Addressing the critical gap in traditional diagnostic methods, our approach deftly navigates the challenges of sensor data anomalies, ensuring robust and accurate real-time health assessments. This innovation not only promises to enhance the reliability and safety of aviation but also sets a new benchmark in the application of intelligent machine-learning solutions in high-stakes environments. Our method is adept at identifying and compensating for data anomalies caused by faulty or uncalibrated sensors, ensuring uninterrupted health assessment. The model employs a simulation-based dataset reflecting complex hydraulic failures to train robust machine learning classifiers for fault detection. The primary tier focuses on fault classification, whereas the secondary tier corrects sensor data irregularities, leveraging redundant sensor inputs to bolster diagnostic precision. Such integration markedly improves classification accuracy, with empirical evidence showing an increase from 95.88% to 98.76% post-imputation. Our findings also underscore the importance of specific sensors—particularly temperature and pump speed—in evaluating the health of landing gear, advocating for their prioritized usage in monitoring systems. This approach promises to revolutionize maintenance protocols, reduce operational costs, and significantly enhance the safety measures within the aviation industry, promoting a more resilient and data-informed safety infrastructure.

Keywords: Fault Diagnosis, Aircraft Landing Gear Systems, Machine Learning, Sensor Data Imputation, Hydraulic Failure Simulation, Safety Enhancement in Aviation, Real-time Health Assessment, Diagnostic Accuracy Improvement.

I. Nomenclature

AI	=	Artificial Intelligence
ML	=	Machine Learning
ICAO	=	International Civil Aviation Organization
ATA 32	=	Air Transport Association Chapter 32: Landing Gear
TapAir	=	Hydraulic fluid-to-air ratio
RPM	=	Revolutions Per Minute
EDA	=	Exploratory Data Analysis
KNN	=	K-Nearest Neighbors
XGBoost	=	Extreme Gradient Boosting

II. Introduction

Aircraft, epitomizing the zenith of modern engineering, comprise an intricate matrix of systems and subsystems functioning cohesively to guarantee a secure flight. At the heart of this matrix lies the landing gear system, an indispensable, non-redundant element of an aircraft's architecture. Acting as a conduit between the aircraft and the ground, it encompasses a range of dynamic components, including the landing gear, wheels, brakes, shock absorbers, retraction mechanisms, control valves, and supplementary systems. Notably, each component within an aircraft is usually complemented by a backup or redundant system to ensure continuity of operation in the event of a malfunction. For instance, should a primary thruster fail, the aircraft can seamlessly switch to an auxiliary thruster, enabling the flight to proceed to the nearest suitable landing site. This redundancy principle applies to various subsystems, such as navigation, communication, power supply, and fuel systems, among others. However, for a paramount system like the landing gear, there exists no alternative or backup mechanism to fall back on in the event of failure. Consequently, it becomes imperative to monitor the health of the landing gear in real-time constantly.

Landing gear health monitoring is vital for passenger safety and economic efficiency in aviation, with 18% of aviation accidents annually linked to landing gear failure, including 756 accidents and 2072 fatalities from 2013-2022 (ICAO) [1]. Traditionally, real-time health assessments have been conducted using both model-driven and data-driven approaches. Model-based methods, despite requiring accurate models, substantial computational resources, and in-depth system understanding, can fail to predict failures in time, as in the 2018 Saudi Airlines A330-200 incident [2]. Conversely, data-driven methods, less dependent on prior system knowledge, can be misled by faulty sensor data, as seen in the 2009 A343 Helsinki incident, where a sensor error led to a misdiagnosis of a hydraulic system leak as too high temperature [3]. These examples underline the need for advanced, real-time, robust health monitoring in aviation.

The existing AI-powered ML models rely heavily on data procured from sensors. If a sensor malfunctions or sustains damage, the input data to the model is inevitably compromised, which can lead to inaccurate health status assessments by the model. For instance, should a system be functioning optimally, but the sensor suffers from wear and tear, the health assessment system may issue a false alarm. Conversely, a faulty sensor might lead the model to incorrectly predict a component failure, when in reality, the component is functioning as intended. In this intricate scenario, the current research aims to design a two-tire intelligent, robust, and data-driven machine learning methodology for real-time fault diagnosis in the landing gear actuation system. The focus is primarily on hydraulic failure modes. The proposed approach strives to accurately detect faults at the component level, manage multimode failure cases, and handle data from faulty and uncalibrated sensors. This methodology markedly diverges from conventional ML practices. The effectiveness of machine learning algorithms for this newly proposed model will be evaluated and compared. The study will also highlight critical sensors for the health assessment of the landing gear, a pivotal aspect of any fault detection system.

III. Literature Review

A. Historical Overview of Landing Gear Health Monitoring

The landing gear system, being a critical component of aircraft, has been the subject of extensive research and development over the past decades. Historically, health monitoring of the landing gear was primarily based on periodic inspections and maintenance schedules [4]. However, with the advent of technology, real-time health monitoring systems have gained prominence. Phillips et al. discussed the evolution of landing gear health monitoring systems, highlighting the transition from manual inspections to automated systems [5]. The study emphasized the importance of real-time monitoring in enhancing aircraft safety and reducing maintenance costs. Boniol et al. provided a comprehensive review of the mechanical and hydraulic components of the landing gear system. They discussed the challenges of monitoring these components and underscored the need for advanced diagnostic systems [6].

B. Model-Driven vs. Data-Driven Approaches in Aircraft Health Monitoring

Historically, model-driven techniques, grounded in mathematical or physical models, have been the mainstay. These models, derived from fundamental principles, offer predictions based on well-established scientific laws. Kang et al. delved into the intricacies of model-driven techniques for predicting landing gear failures. Their research highlighted the challenges of modeling complex interactions within the landing gear system. They argued that while these models provide a structured framework, their rigidity can sometimes be a limitation, especially when faced with unforeseen system behaviors [7]. Chen et al. presented a comprehensive model of an aircraft's hydraulic system. Their study demonstrated the efficacy of model-driven approaches in predicting system behavior under various conditions but also underscored the challenges in achieving high model fidelity [8]. With the proliferation of sensors and advancements in computational techniques, data-driven methodologies have gained significant traction. David and Nita showcased the potential of deep learning algorithms in aircraft health monitoring. Their study emphasized the superior performance of data-driven models, especially in identifying nuanced faults that traditional models might overlook. They highlighted the adaptability of these models, especially when trained with diverse and extensive datasets [9]. Dangut et al. took a critical look at data-driven health monitoring systems in aviation. Their research underscored the importance of data quality and robust preprocessing techniques. They pointed out that while data-driven models are powerful, their efficacy is heavily contingent on the quality of the input data. Faulty sensors or inconsistent data can significantly compromise the accuracy of these models [10]. While both methodologies have their strengths, their performance of then in real-time on-board systems discourse seems to be leaning towards the potential of data-driven techniques. The adaptability, scalability, and pattern recognition capabilities of these models make them particularly suited for modern aircraft health monitoring systems. However, as Zhao et al. pointed out, the success of these models hinges on the quality of data, emphasizing the need for robust data acquisition and preprocessing systems [11].

C. AI and ML in Aircraft Health Monitoring: A Focus on Hydraulic Systems

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in aircraft health monitoring with the advancement of a data-driven approach, especially concerning hydraulic systems, has been a transformative force in recent years. Jacazio et al. explored the application of ML algorithms specifically tailored for hydraulic system diagnostics. Their research highlighted the potential of data-driven models in detecting subtle anomalies within the hydraulic flow and pressure data, which traditional methods might overlook [12]. Kenan and Zhao further emphasized the advantages of using deep learning techniques, such as Convolutional Neural Networks (CNNs), for analyzing time-series data from hydraulic sensors. Their methodology demonstrated superior accuracy in predicting hydraulic system failures, especially in scenarios with complex, non-linear patterns [13]. Swischuk and Allaire discussed the challenges posed by sensor drift, calibration errors, and outright failures in hydraulic systems. Their study revealed that even minor discrepancies in sensor readings could lead to significant misdiagnoses, potentially compromising aircraft safety [14].

D. Limitations and Gap in current knowledge

The vast landscape of aviation research has seen numerous studies focusing on the health monitoring of aircraft systems, particularly the landing gear. However, a closer examination of the existing literature reveals certain limitations: **Handling Faulty Sensor Data** - Despite the advancements in AI and ML for aircraft health monitoring, there's a pressing need for methodologies that can effectively handle and rectify faulty sensor data in real-time; and **Two-Tier ML Model** - The concept of a two-tier ML model, as highlighted in the introduction, remains a novel idea. Existing practice has not ventured into the development of such a model that first rectifies anomalies in sensor data before making health assessments.

The aspiration to provide a proof of concept, to showcase intelligent sensor data management can transform the aviation industry, is the driving force behind this research. As we transition to the methodology of our groundbreaking approach, it is essential to underscore the significant contributions this research makes in addressing the prevailing limitations and gaps in aircraft landing gear diagnostics. Traditional diagnostic methods in the aviation industry have often been constrained by their inability to accurately interpret complex sensor data, particularly under the duress of faulty or inconsistent readings. Our research directly addresses these challenges by introducing an innovative two-tier machine learning model, which not only enhances the accuracy of fault diagnosis but also pioneers the management of sensor data anomalies in real-time. This approach not only fills a critical void in existing diagnostic practices but also paves the way for a more resilient, reliable, and safer aviation future. As we delve into our methodology, we present a detailed blueprint of how our model innovatively navigates these complexities, setting a new standard in aircraft system health assessment.

IV.Methodology

In the realm of predictive maintenance, the precision and clarity with which one can predict a system's health can dramatically influence operational efficiency, safety, and costs. As technological advancements continue to surge, the domain has seen a pivotal shift towards leveraging sophisticated machine learning models to harness data-driven insights. However, challenges such as data imperfections often impede the application of these models in real-world scenarios. Addressing these concerns requires a systematic, well-thought-out approach, which our research offers.

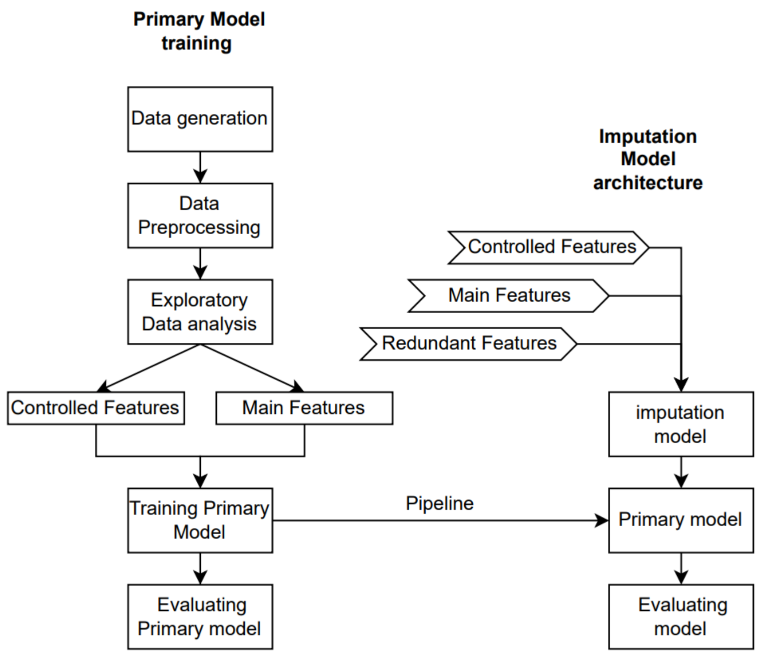

Fig. 1 High-level system architecture.

To facilitate a seamless understanding of our proposed approach, we begin our methodology with a high-level schematic representation in Figure 1. This diagrammatic overview elucidates the interplay between our two-tier model system: the primary classification model, dedicated to fault classification, and the secondary imputation model, designed to handle data imperfections through intelligent preprocessing techniques. This visual aid garners a holistic understanding of the data flow, model interactions, and the sequence in which the system operates, before diving deep into each methodological component.

A. Data generation

The cornerstone of this research methodology is the meticulous collection of data that portrays a broad range of operational states associated with landing gear extension and retraction systems. The absence of real-time faulty landing gear operations data poses considerable challenges, that underscore the pivotal role of simulation tools. Such tools not only present an avenue to simulate the dynamics of landing gear operations with precision but also facilitate the accumulation of crucial data for the training of ML models. In our approach, we utilize the "Landing Gear Model in Simscape" provided by Simulink MATLAB [15]. This tool, a product of Steve Miller's team's expertise, stands out for its accuracy and comprehensive representation of the system dynamics. For the robust training of our ML model, it's essential to simulate a wide array of scenarios, particularly those indicative of failure states. Our model was adapted to encompass 370 distinct failure scenarios, systematically categorized into 12 defined failure types. Given that real-world environments are often affected by noise, our simulations deliberately introduce noise to sensor readings, enhancing the realism of our dataset.

Our design encompasses both singular mode and multimode failure conditions, ensuring the dataset captures a broad spectrum of system behaviors, vital for the machine learning model's efficacy as shown in table 1.

Table 1. Classification of Fault Scenarios in Aircraft Landing Gear Systems

Scenario Number	Scenario Type	Faulty Scenario	Description
1	Single-mode	No fault condition	Standard operational mode
2	Single-mode	Pump failure condition	Pump malfunction
3	Single-mode	Very high-temperature condition	Elevated temperature readings
4	Single-mode	Faulty pump condition	Degraded pump performance
5	Single-mode	Oil leakage condition	Hydraulic fluid compromises

6	Multi-mode	Faulty pump and very high temperature	Degraded pump performance concurrent with elevated temperatures
7	Multi-mode	Pump failure and very high temperature	Pump malfunction in tandem with very high-temperature readings
8	Multi-mode	Oil leakage and very high temperature	Compromised hydraulic fluid accompanied by high temperature conditions
9	Multi-mode	Oil leakage and pump failure	Hydraulic fluid breaches coupled with pump malfunctions
10	Multi-mode	Faulty pump and oil leakage	Degraded pump operations simultaneous with hydraulic fluid compromises
11	Multi-mode	Oil leakage, pump failure, and very high temperature	Triple anomaly of hydraulic fluid breaches, pump malfunction, and elevated temperatures
12	Multi-mode	Faulty pump, oil leakage, and very high temperature	Degraded pump operations alongside hydraulic fluid breaches and high temperature readings

In the upcoming subsections, we will elaborate on the simulation's overview, delve into fault and noise injections, and finally highlight the distinct features of our collected data.

B. Overview of simulation

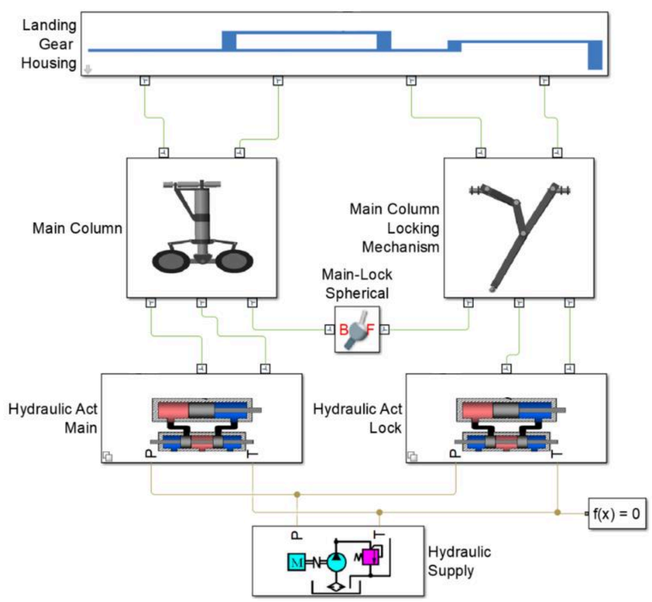

Fig. 2 Block diagram of the simulation

The employed simulation model accurately reflects the ATA 32 standard in aircraft systems, which covers all aspects of landing gear, including hydraulics, structure, brakes, and steering. For this study, however, we focus solely on the hydraulic system. A top-level layout of the simulation component is provided in Figure 2.

It comprises a single hydraulic pump powered by an electric motor. The hydraulic reservoir supplies fluid to the main actuator, responsible for extending and retracting the landing gear based on pilot commands. Upon deployment, a secondary or locking actuator activates, securing the main landing gear in place, which is crucial for safety. The simulation also includes several sensors that measure factors like pressure, angular movement, valve status, and extension levels. A time series snapshot of the landing gear extension and retraction cycle simulation is shown in Figure 3. This simulation allows us to adjust the temperature of the hydraulic fluid, hydraulic pump speed and the ratio of fluid-to-air in the hydraulic system simulation component. This is to study how temperature changes might affect the system's performance. Additionally, the TapAir feature lets us modify the hydraulic fluid-to-air ratio, simulating various real-world conditions, which will be discussed in detail later. To simulate different failure cases, we will be adjusting three primary parameters: the pump speed, the fluid temperature, and the TapAir ratio.

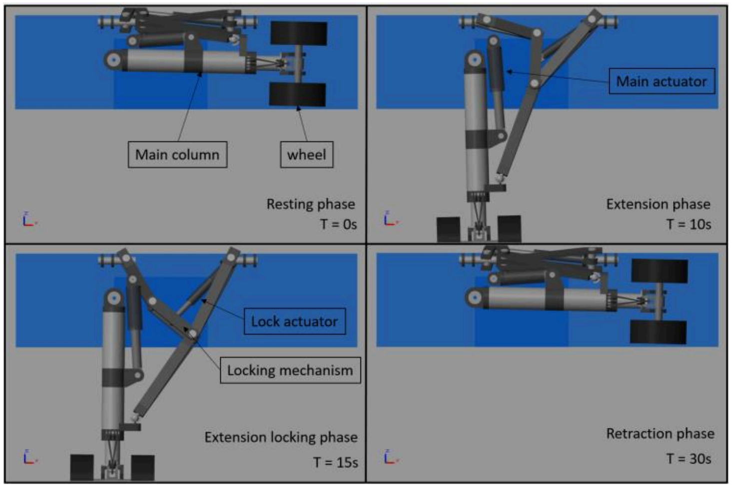

Fig. 3 Timeseries snapshot of a simulation showing the different phases of Landing gear operation

C. Fault Injection into the Simulation

Our research delves deeply into simulating conditions within a hydraulic system, both faulty and non-faulty. We focus on three core operational parameters: TapAir ratio, pump speed, and system temperature. We explore a range of scenarios, from typical normal operations to compound faults - we have defined 12 scenarios below, of which 11 are faulty as depicted in Figure 4.

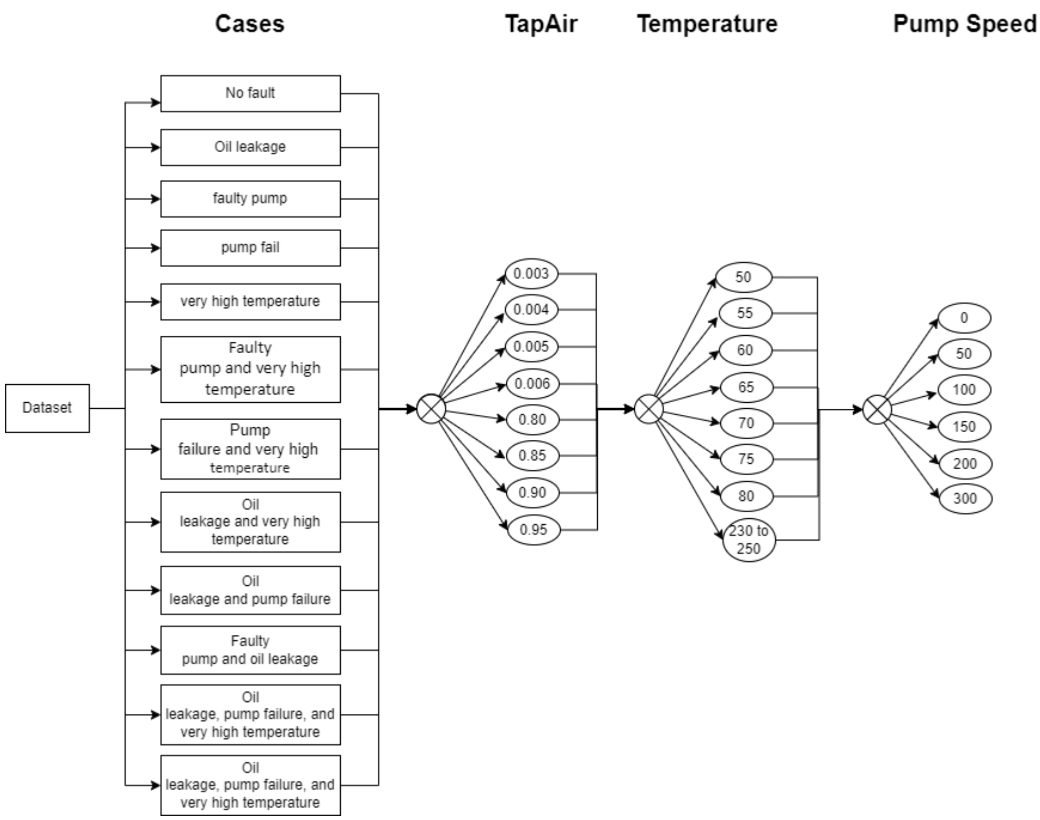

Fig. 4 Fault injection strategy by different combination of 3 controlled parameters

Table 2. Summary of Fault Scenarios and Indicators in Aircraft Hydraulic Systems

Scenario Number	Faulty Scenario	Key Parameters	Indications
1	No Fault	Temp: 50-80°C, TapAir: 0.003-0.006, RPM: 300	Routine functioning, system in good health
2	Oil Leakage	TapAir: 0.80-0.95	Significant oil displacement, leakage suspected
3	Faulty Pump	RPM: 50-200	Pump malfunction, reduced speed
4	Pump Failure	RPM: 0	Complete pump cessation
5	Very High Temperature	Temp: 223-250°C	Potential overheating or cooling failure
6	Faulty Pump and Oil Leakage	RPM: 50-200, TapAir: 0.80-0.95	Reduced pump speed with significant oil leakage
7	Faulty Pump and Very High Temp	RPM: 50-200, Temp: 223-250°C	Reduced pump function with very high temperatures
8	Oil Leakage and Very High Temp	TapAir: 0.80-0.95, Temp: 223-250°C	Significant oil leakage with elevated temperatures
9	Oil Leakage and Pump Failure	TapAir: 0.80-0.95, RPM: 0	Complete pump halt with oil displacement
10	Pump Failure and Very High Temp	RPM: 0, Temp: 223-250°C	Halted pump with skyrocketing temperatures
11	Oil Leakage, Pump Failure, Very High Temp	TapAir: 0.80-0.95, RPM: 0, Temp: 223-250°C	Pronounced oil leakage, pump halt, and extreme temperatures
12	Faulty Pump, Oil Leakage, Very High Temp	RPM: 50-200, TapAir: 0.80-0.95, Temp: 223-250°C	Malfunctioning pump, significant oil leakage, heightened temperatures

D. Sensor Noise Injection

Within our utilized simulation, sensors were characterized as ideal, devoid of any noise. Contrarily, in practical applications, sensors invariably exhibit noise in their outputs. To enhance the fidelity of our simulation to real-world scenarios, we incorporated components that superimpose noise onto the sensor signals. Specifically, we introduced a 15% white noise to each sensor's output. This adjustment ensures our simulation more accurately reflects the inherent interference often encountered in actual sensor systems. Figure 5 plots an ideal signal, free from noise, against one subjected to our introduced noise, illustrating the tangible modifications that can be seen.

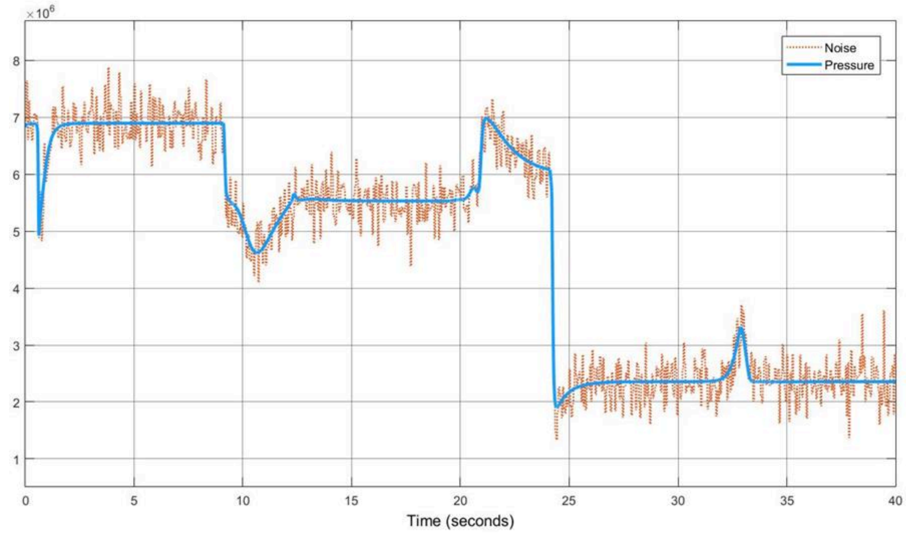

Fig. 5 Comparison of signal without and with noise injection in pump pressure.

E. Features of the collected Data

The comprehensive dataset extracted from a series of simulations consists of 10 features, one of which is 'health,' the target variable for our classification model. These features serve as inputs for the machine learning model. Detailed information about each feature, including the corresponding sensor and its location within the simulation, is provided in the table 3:

Sl no.	Feature	Sensor	Location
1	Time	Independent feature	N/A
2	Main Actuator Pressure 1	Pressure sensor	Main Actuator
3	Main Actuator Pressure 2	Pressure sensor	Main Actuator valve
4	Pump Pressure	Pressure sensor	Hydraulic tank
5	Main Column Angle 1	Rotary encoder	Junction of landing gear housing and main actuator
6	Main Actuator Position 2	Linear Variable Differential Transformers (LVDT)	Main Actuator
7	Pump Torque	Optical Torque Sensors	Mounted on top of pump motor
8	Temperature	Input parameter	N/A
9	Pump Speed	Input parameter	N/A
10	Health	Condition label	N/A

Table 3. List of all features in the collected data and their details

Further association of these features and their importance in assessing the health of the system will be explored in the next section: Exploratory data analysis and Data pre-processing.

F. Exploratory data analysis and Data pre-processing

Exploratory Data Analysis (EDA) is more than just an initial step in the data analysis pipeline; EDA is crucial for understanding data structures, relationships, anomalies, and patterns. It is particularly effective in identifying and managing redundancies in sensor data, where multiple sensors may record similar information. This redundancy, while typically a safety feature, can be overwhelming and needs careful analysis to ensure efficient data use and cost savings. Traditional approaches might suggest discarding highly correlated data to avoid multicollinearity in machine learning models. However, this study proposes using EDA to create innovative strategies that utilize rather than discard redundant data. For instance, primary models are trained with main features, and secondary models with correlated, redundant data. This method improves model robustness, ensuring continuous monitoring even if a primary sensor fails, and makes efficient use of data, enhancing the model's richness and reliability. In our analysis, the correlation values are derived using the Pearson Correlation Coefficient, a measure of linear association between two variables, the coefficient can vary between -1 and 1, providing insights into the nature of the relationship, coefficient 1 Indicates a perfect positive linear relationship, whereas -1 indicates negative linear relationship and 0 suggests no linear association between the two variables. Refer to Figure 6 below, which displays a heatmap visually representing the correlation coefficients among the numerical features of our dataset.

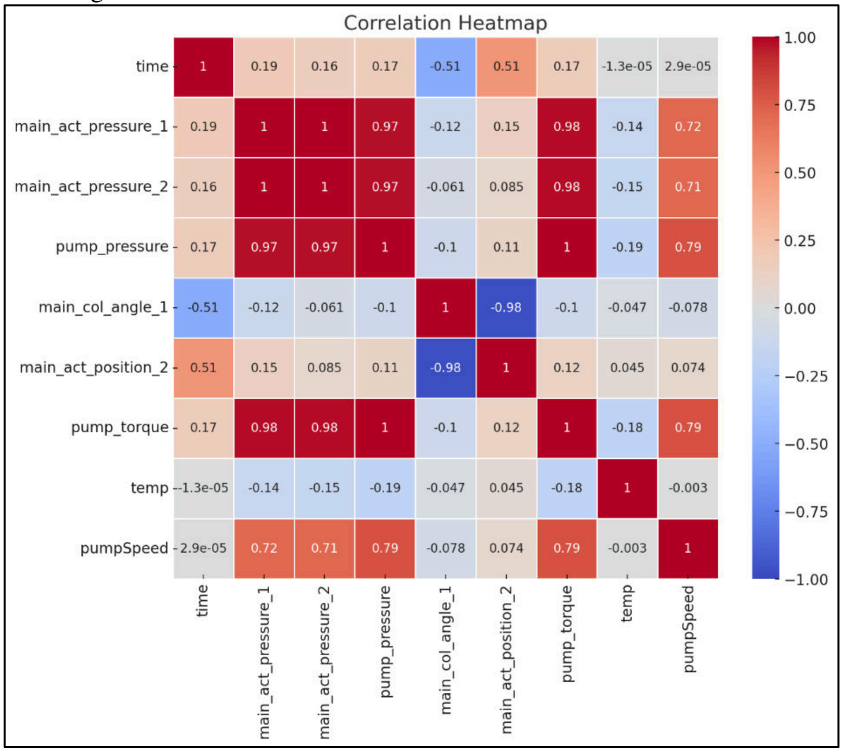

Fig. 6 Correlation Heatmap

The correlation heatmap elucidates the intricate relationships among the dataset's features:

1. **High Correlations:** Feature pairs like pump_pressure & pump_torque, main_act_pressure_1 & main_act_pressure_2, and main_col_angle_1 & main_act_position_2 exhibit strong correlations.
2. **Distinct Features:** Some features, notably pumpSpeed and temperature, show limited correlation with others, underscoring their unique significance.

Spotting and Understanding Redundancies:

1. **Pump Pressure and Pump Torque:** With a correlation of 0.998381, these two exhibit an almost perfect positive relationship. A time series plot of pump pressure and torque of one of the cases is plotted in the figure 7, where they exhibit the identical pattern. This suggests that pump pressure can precisely predict pump torque, potentially rendering one redundant in predictive modeling.

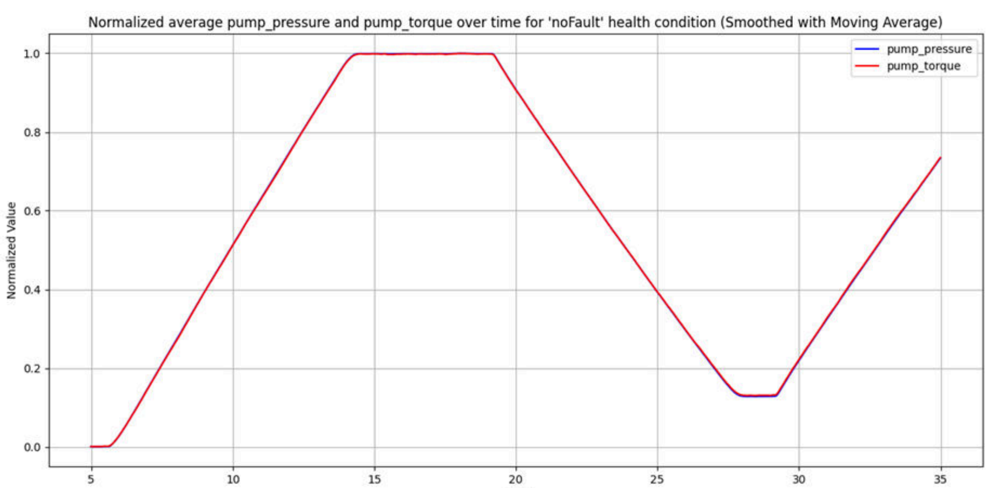

Fig. 7 Moving averages of normalized pump pressure and pump torque.

2. **Main Actuator Pressure 1 and Main Actuator Pressure 2:** A robust positive correlation of 0.996350 signifies that one can reliably predict the other, hinting at potential redundancy. A time series plot of Main Actuator Pressure 1 and Main Actuator Pressure 2 of one of the cases is plotted in the figure 8, where they exhibit nearly the identical pattern.

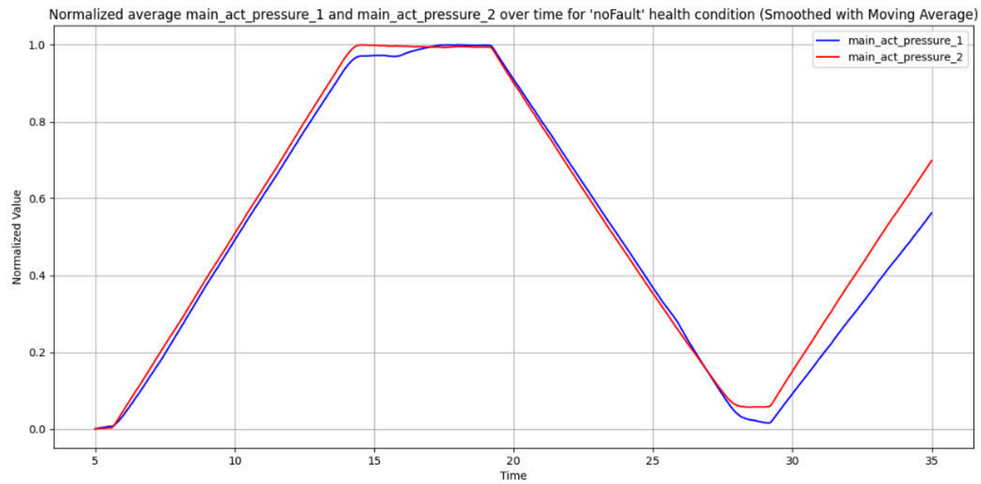

Fig. 8 Moving averages of normalized main actuator pressures 1 and 2.

3. **Main Column Angle 1 and Main Actuator Position 2:** A significant negative correlation of -0.983905 suggests an impeccable inverse relationship. As one variable's value rises, the other's falls, indicating mutual predictability. A time series plot of Main Column Angle 1 and Main Actuator Position 2 of one of the cases is plotted in the figure 9, where they exhibit exact mirror pattern.

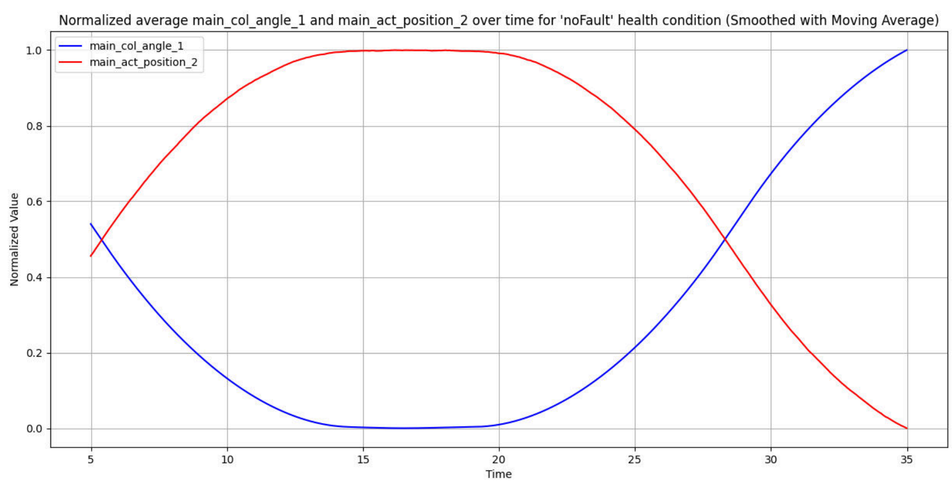

Fig. 9 Moving averages of normalized main column angle 1 and Main Actuator Position 2.

4. Features like temp and pumpSpeed have relatively low correlations with other features, suggesting they are more unique and independent without any redundancy. We call these features as crucial or controlled features. Note that these two are the input variables that we used in simulation to simulate wide range of failure scenarios.

The rationale behind feature selection and tagging for a model focused on the health of a system is detailed. Temporal elements are excluded to focus on current system states, making the model robust against temporal disturbances. The target variable is the system's health. Features are categorized into controlled (pump speed, temperature), main (pump pressure, main actuator pressure, main column angle), and redundant (pump torque, secondary actuator pressures and positions), with the latter serving as backups for enhanced reliability. An innovative approach uses both main/controlled and redundant features in primary and secondary models, respectively, ensuring continuous monitoring even if a main sensor fails. This strategy reflects a deep understanding of the system and sensor-based monitoring, aiming for a robust and resilient model. The dataset is divided into 70% for training, 20% for testing, and 10% for evaluation, with the latter being unseen during training to accurately assess model performance. The next phase of the research focuses on model selection and architecture, crucial for extracting insights from the data.

G. Primary Model Selection for Aircraft Landing Gear Health Prediction: A Comparative Approach

Our research aims to predict the health status of aircraft landing gear systems using a classification model. We selected a diverse set of classifiers, each offering unique advantages in handling the dataset's complexities.

Each classifier was strategically selected to capture both linear and non-linear relationships in the dataset. The combination of foundational models like Logistic and Polynomial Regression with more complex models like Decision Trees, KNN, Random Forest, and XGBoost ensures a comprehensive understanding of the dataset. This multifaceted approach paves the way for robust predictions in aircraft landing gear health. The subsequent sections will detail a performance analysis, comparing these classifiers' efficacy in the context of our specific application.

H. Secondary Model – Imputation Model

Sensor data often contains inconsistencies, missing values, and errors. Our Imputation Model, a secondary layer, addresses these issues to maintain data integrity and consistency. Traditional methods might overlook or average out faulty or missing data, which is not viable for complex systems such as aircraft landing gears where every data point is crucial. The Imputation Model intelligently fills data gaps, ensuring that machine learning processes downstream receive a complete, reliable, and robust dataset.

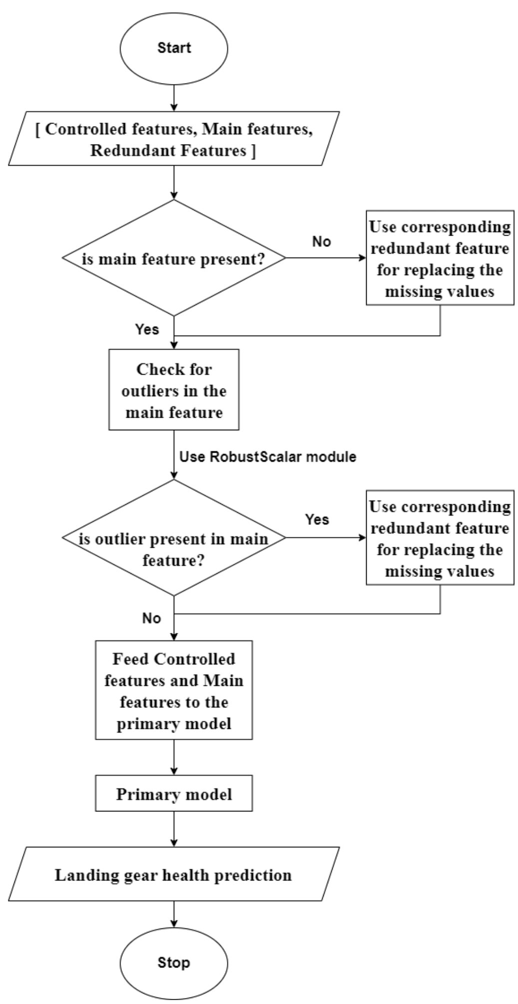

Fig. 10 Data Flow Logic in Imputer Model to Primary Model

The model uses a pre-defined data structure with three categories of features: Controlled (e.g., pumpSpeed, temp), Main (e.g., pump_pressure, main_act_pressure_1), and Redundant (e.g., pump_torque, main_act_pressure_2). It processes 8 parameters from these features. The Simple Imputer logic first checks the reliability of main features. If missing, it replaces them with redundant features. If present, it checks for outliers using a Robust Scalar trained on the test dataset which is typically caused by uncalibrated sensors. Outliers are substituted with redundant feature values before passing the data to the primary model for classification. The preprocessed dataset, now composed of controlled and processed main features, is input into our primary machine learning model. This model, trained specifically on these features, evaluates the landing gear system's health. For a comprehensive analysis, the primary model is integrated with the imputation model, and their combined effectiveness is validated using a separate dataset.

V. Results and Discussion

Our groundbreaking two-tier model, which includes a primary classification model followed by a secondary imputation model, is tailored for the complexities of aircraft landing gear simulations. This section will explore the individual and combined performances of these models, showcasing their industry-leading capabilities. We assess the model using various classifiers, and the results, detailed in Table 4, affirm its superiority in handling complex datasets.

Algorithm	**Test Accuracy Without Imputation**	**Validation Accuracy Without Imputation**	**Test Accuracy with Imputation**	**Validation Accuracy with Imputation**
Logistic Regression	66.53%	64.24%	72.82%	72.09%
Polynomial Regression	78.65%	79.52%	83.91%	86.72%
Decision Tree	95.88%	91.45%	98.76%	93.93%
KNN	90.57%	89.02%	94.22%	92.87%
Random Forest	96.51%	91.36%	99.11%	92.98%
XGBoost	96.05%	85.92%	98.64%	87.83%

Table 4. Summary of Model Performances

A. Evaluating the Primary Classification Model

The primary classification model underwent rigorous testing using various algorithms, revealing significant insights:

1) **Logistic Regression:** Exhibited decent performance (Test: 72.82%, Validation: 72.09%), indicating basic pattern recognition but a potential underestimation of data complexity.
2) **Polynomial Regression:** Demonstrated superior handling of non-linearities (Test: 83.91%, Validation: 86.72%), suggesting its effectiveness in more complex scenarios.
3) **Advanced Models (Decision Tree, KNN, Random Forest, XGBoost):** These models achieved exceptionally high accuracy (up to 99.11% on test data), underlining their power in capturing intricate data relationships. However, some overfitting issues were noted, particularly in Decision Trees and XGBoost, which necessitates careful regularization and hyperparameter tuning.

These findings highlight the critical role of model selection, balancing accuracy, interpretability, and real-world applicability.

B. Breakthrough with the Secondary Imputation Model

By examining the accuracy metrics of the primary classification algorithms both with and without the imputation layer as depicted in the table 2 above, a clear enhancement in performance can be observed:

- **Performance Enhancement:** Across all classifiers, the introduction of the imputation model led to significant improvements in accuracy (e.g., Logistic Regression test accuracy rose from 66.53% to 72.82%).
- **Holistic Data Management:** This model's effectiveness in refining data integrity substantially boosted the overall system performance.
- **Real-World Applicability:** The model adeptly addresses common issues in aircraft simulations, like sensor anomalies, enhancing reliability and confidence in the results.
- **System Dynamics Understanding:** The success of the two-tier system lies not just in mathematical modeling but also in a deep understanding of aircraft system dynamics.

This improvement in accuracy metrics underscores the transformative impact of the secondary imputation model on the primary classifiers. Our research offers a novel and robust approach to analyzing aircraft landing gear systems. The two-tier model, with its exceptional accuracy and adaptability, stands as a pioneering solution in the industry. Future research may delve into refining imputation strategies or integrating cutting-edge algorithms, further enhancing this already impressive model.

C. Significance of Key Sensors and Their Economic Implications

In our extensive study on aircraft landing gear health assessment, the temperature sensor and the pump speed measurement sensor emerged as pivotal elements. These sensors are not mere tools for data collection; they are the linchpins ensuring optimal aircraft performance and, most importantly, passenger safety. These two specific sensors are absent in traditional ATA 32 landing gear architecture. This study signifies the need to capture the temperature and speed of hydraulic pumps plays a crucial role, hence the focus has to be given by the aviation industry for the integration of the above-mentioned sensors along with their redundant sensors. From an economic standpoint, integrating these sensors into existing aerospace models presents a transformative opportunity. Accurate readings can preempt potential issues, translating to significant savings by preventing prolonged aircraft downtimes and expensive repairs. An upfront investment in retrofitting existing aircraft with advanced sensors can lead to long-term benefits, including reduced maintenance costs and a prolonged aircraft lifespan. Additionally, in an industry where reputation is paramount, airlines equipped with state-of-the-art sensors stand out, promoting passenger trust and brand loyalty.

VI. Conclusion

This research aims to develop a robust model for health assessment through sensor data analysis. Central to our methodological approach was the two-tier system: a primary classification model strengthened by a secondary imputation model. In the vast expanse of sensor data, inconsistencies and anomalies are inevitable. The introduction of our imputation model, tailored to fill these data gaps intelligently, proved to be a game-changer, ensuring data integrity and consistency. Our comprehensive evaluation of various classifiers highlighted the nuanced nature of our dataset, with results indicating clear variances in performance. Notably, ensemble methods like Random Forest and XGBoost showcased impressive accuracies on the training set. Still, the overarching narrative emphasized the necessity of a balance between achieving high accuracy and preventing overfitting. Furthermore, the pivotal role of temperature and pump speed measurement sensors emerged as a cornerstone for accurate predictions. Their importance transcends mere technical functionalities, extending to significant economic ramifications for the aerospace industry. Proactive investments in these sensors can lead to substantial long-term operational savings and heightened safety standards. In essence, this study sheds light on the profound impact of strategic data handling and the role of specific sensors in the ever-evolving domain of aerospace systems. The insights garnered not only propel the aerospace sector toward enhanced safety protocols but also underline the symbiotic relationship between technology and economic efficiency. Future endeavors in this field would do well to remember that in the delicate dance of machinery, every data point, every sensor, holds the potential to shape the future of air travel.

Appendix

Addressing Overfitting in Model Training

In the development of our machine learning models, a paramount consideration was the risk of overfitting, given the substantial size of our dataset (671,907 samples). To mitigate this, we employed several strategies:

- **Cross-Validation**: We integrated k-fold cross-validation into our model training process. This approach not only validates the model’s effectiveness across different subsets of the data but also ensures that the model does not overfit to specific segments of the dataset.
- **Regularization Techniques**: In models such as Decision Trees and Random Forests, we optimized parameters like **max_depth** and **n_estimators** respectively. These parameters act as constraints on the models, preventing them from becoming overly complex and tailored to the training data.
- **Robust Scaling**: Utilizing RobustScaler minimizes the influence of outliers, which can lead to overfitting by skewing the model’s perception of data distribution.

Dataset Distribution

Our dataset's distribution is characterized by a diverse range of operational scenarios, essential for training robust models:

- **Even Distribution of Health Conditions**: Each health condition category within the dataset is represented by approximately 54,000 to 60,000 samples, ensuring a balanced approach to model training.

Hyperparameters for Primary Model Training

In training our primary models, we used a variety of machine learning algorithms, each with its set of hyperparameters:

- **Decision Tree Classifier**: Set with a fixed **random_state** for reproducibility. Future work could explore optimizing **max_depth** for more controlled tree growth.
- **Random Forest Classifier**: Employed with a default **random_state**. Parameters like **n_estimators** and **max_features** would be key areas for hyperparameter tuning in further studies.
- **XGBoost Classifier**: Configured with **use_label_encoder=False**, **eval_metric="logloss"**, and a consistent **random_state**. Important parameters for future tuning include **learning_rate** and **n_estimators**.
- **K-Nearest Neighbors (KNN) Classifier**: Used with default parameters, with potential for tuning the **n_neighbors** parameter.
- **Logistic Regression**: Implemented with **solver='lbfgs'** and an increased **max_iter=5000**. The regularization strength parameter **C** could be a focus for future optimization.

These details on model training, dataset distribution, and hyperparameter settings are pivotal in underscoring the robustness and reliability of our methodology, ensuring that our models are well-suited for the complex task of fault diagnosis in aircraft landing gear systems.

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2024-01-04

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Kadripathi KN, Ignatyev D, Tsourdos A, Perrusquia A. (2024) Advancing fault diagnosis in aircraft landing gear: an innovative two-tier machine learning approach with intelligent sensor data management. In: AIAA SCITECH 2024 Forum, 8-12 January 2024, Orlando, USA. Paper number AIAA 2024-0759

https://doi.org/10.2514/6.2024-0759