Fault Injection for Synthetic Data Generation in Aircraft: A Simulation-Based Approach

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***Abstract*—The safety of aircraft heavily depends on the integrity of the Landing Gear System (LGS). However, gathering real-world fault data to support effective Prognostic and Health Management (PHM) practices presents significant challenges. This work proposes a novel methodology for generating synthetic fault data using a multi-physics Simscape model of a landing gear deployment/retraction mechanism. The model incorporates specialized fault blocks designed to replicate various hydraulic failure modes, aiming to broaden the pool of fault data covering the most common failures. This approach promises to enhance maintenance strategies and facilitate the development of hybrid Model-Based and Data-Driven solutions. Ultimately, the results of this study will be used to understand the physics within the landing gear better and gather the necessary data to create an effective Digital Twin for predictive maintenance.**

***Index Terms*—Landing Gear System, Fault Injection, Synthetic Data**

I. Introduction

LANDING gear systems ensure aircraft safety during the critical takeoff and landing phases. These systems, accounting for 2.5%-5% of the maximum takeoff weight and 1.5%-1.75% of the aircraft's cost, disproportionately contribute to 20% of the airframe's direct maintenance costs [1], [2]. Hydraulic systems are mainly utilized for landing gear retraction/extension due to their proficiency in achieving smooth and precise speed control. However, ensuring the integrity and functionality of these systems necessitates robust fault detection and diagnosis strategies. The traditional *time-based maintenance* approach for aeronautical systems is undergoing a significant paradigm shift. By 2035, *condition-based maintenance* is expected to become the standard, with a further transition towards *predictive maintenance* utilizing Artificial Intelligence (AI) algorithms for real-time health monitoring [3]–[5]. This shift relies heavily on the availability of a vast amount of high-quality data, encompassing both healthy and faulty system behavior. However, acquiring or accessing real-world fault data from intricate aircraft systems like landing gear is challenging and often cost-prohibitive [6]. Deliberately causing faults in real systems can be unsafe and infeasible, rendering simulation a critical tool. The aviation industry has decades of experience with model-based design, making it a natural fit for fault injection.

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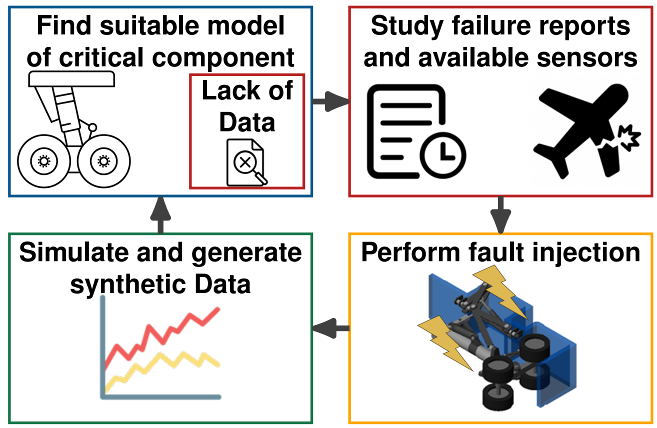

Figure 1: Overview of the proposed methodology to model and inject multi-domain faults into the landing gear systems through differential equations to generate fault synthetic data.

This work adopts a model-based approach to investigate the consistency between a system's actual and expected behavior in LGS. We introduce a novel methodology for gathering synthetic fault data by employing fault injection techniques within an LGS model (see Figure 1). This approach facilitates the generation of synthetic fault data, bridging the gap imposed by the limitations of real-world data acquisition and enabling the exploration of a wide array of potential failures [7]. The generated synthetic data, encompassing both healthy and faulty system behavior, is instrumental in developing and validating robust PHM algorithms for future LGS, paving the way for a future of predictive maintenance in aviation.

The contributions of this research are delineated as follows:

- **Model-Based Fault Analysis with Synthetic Data Generation**: The work leverages a model-based approach for fault analysis in LGS. This approach is particularly valuable due to the limitations of acquiring real-world data for all possible fault scenarios. The study introduces a methodology for gathering synthetic fault data by employing fault injection techniques within the model. This

methodology can be adapted to cover a broad spectrum of potential failures in various critical aircraft components, not limited to LGS.
- **Focus on Practical Relevance**: The selection of fault scenarios for detailed analysis prioritizes those with a high impact on real-world LGS operations. This ensures the findings' practical relevance and applicability to improving landing gear safety and reliability.
- **Foundation for Future Research**: The study establishes a foundation for future research in LGS health management. The generated synthetic fault data paves the way for developing and refining robust predictive maintenance algorithms. Additionally, the research highlights the potential of merging model-based and data-driven approaches for even more effective LGS health management strategies.

While this research focuses on aircraft subcomponents, the proposed methodology can be applied to Cyber-Physical Systems and Industrial Cyber-Physical Systems, showcasing its versatility and relevance across domains where fault tolerance and system integrity are paramount.

The rest of this paper is organized as follows: Section II provides comprehensive background information on the aircraft's maintenance evolution, the actual state-of-the-practice on Simulink/Simscape, and multi-domain fault injection. Section III details the adopted methodology. Section IV describes the case of the study and the experiments made. Section V describes the discussion, and VI the conclusion.

II. Background

This section provides some background on the evolution of the maintenance paradigm in aircraft protocol, Simulink, and multi-domain fault injection.

A. Evolution and challenges in aircraft maintenance

The aviation sector stands at the threshold of a significant transformation, driven by the advancements in condition-based and predictive maintenance methodologies. This evolution reflects a broader industry trend towards embracing real-time, data-driven strategies for aircraft maintenance, which promises to redefine operational efficiencies and safety protocols. Central to this shift is the vision articulated by the Advisory Council for Aviation Research and Innovation in Europe (ACARE), which envisions condition-based maintenance becoming the state-of-practice by 2035 [5]. ACARE's projection is not merely aspirational but signals a decisive move towards adopting maintenance frameworks that are adaptive, predictive, and optimized for the dynamic demands of aviation operations. Presently, the industry largely operates under time-based maintenance protocols, where maintenance activities are scheduled at fixed intervals, regardless of the actual condition of the aircraft components. This approach, while systematic, often leads to either over-maintenance or under-maintenance, with the former incurring unnecessary costs and the latter posing risks to safety and reliability. Time-based maintenance's reliance on predetermined schedules rather than real-time data and condition monitoring represents a significant area where efficiency gains can be realized. The limitations of time-based maintenance have become increasingly apparent in light of the burgeoning capabilities for data collection and analysis offered by modern aircraft. These technological advances provide a compelling case for transitioning to condition-based and predictive maintenance methodologies, where decisions are informed by the actual wear and performance of aircraft systems. This transition is not merely technical but is also financial, with the industry grappling with the cost implications of maintenance strategies. In 2018 alone, airlines globally expended approximately $69 billion on maintenance, repairs, and overhaul, accounting for 9% of their total operational costs, as underlined in a recent review [6].

The escalation in maintenance requirements and data collection capabilities presents both a challenge and an opportunity for leveraging big data and AI technologies to enhance efficiency and reduce operational costs. With its foundation in real-time data analytics and extensive sensor networks, predictive maintenance promises to revolutionize aircraft maintenance by preempting equipment failures and optimizing repair schedules, enhancing operational safety and efficiency. Yet, this promising transition is fraught with complexities. Integrating AI and Machine Learning (ML) into predictive maintenance strategies entails navigating the burgeoning complexity of aircraft systems and the voluminous data they generate. The stark contrast between older aircraft models with fewer sensors and newer, more sensor-laden models necessitates adaptive predictive maintenance approaches, ensuring maintenance practices evolve alongside technological advancements.

The review also underscores the burgeoning potential and existing hurdles of predictive maintenance in aviation [6]. A critical challenge emerges in the scarcity of publicly available datasets for aircraft-specific components, especially hydraulics, which play a pivotal role in critical systems like landing gear. This scarcity hinders the development of bespoke predictive maintenance algorithms, emphasizing the need for industry-wide collaboration and open data initiatives. Further, studies comparing ML algorithms against hydraulic system data reveal an intriguing insight: traditional methods with feature engineering often surpass deep learning models in data-constrained scenarios. This not only highlights the limitations of current AI approaches but also points to the potential of hybrid methodologies that blend traditional model-based techniques and data-driven ML techniques for predictive maintenance.

B. Fault modeling using Simulink/Simscape

In the domain of aviation engineering and simulation, the Matlab environment, particularly through its Simulink and Simscape platforms, has established itself as a cornerstone for design, visualization, and testing [8]. The importance of these tools in the avionic world cannot be overstated, facilitating everything from initial design phases to comprehensive Hardware-in-the-Loop testing. A demonstration of their utility is seen in the development of digital twins of an aircraft in 2019 [9]. This achievement underscores the critical role that Matlab and its associated tools play in advancing aerospace engineering and simulation practices. Simulink, renowned for its signal flow-based or causal modeling capabilities, facilitates the connection of system components via signals. This modeling paradigm, where signals transmitted between components are clearly defined, allows for straightforward simulation of system behaviors based on fixed input-output relationships.

The recent introduction of fault injection capabilities into the Simulink platform with the 2023b update marked a significant advancement in simulation technology, allowing engineers and researchers to systematically introduce and study the effects of faults within their models. This feature enables the simulation of various fault conditions without modifying the original system design, offering a powerful means of conducting safety analyses, such as Failure Mode and Effects Analysis (FMEA), and optimizing fault detection and mitigation strategies. Simscape, extending Simulink's capabilities into physical modeling, adeptly handles the heterogeneity of cyber-physical systems by adopting an equation-based approach to represent complex physical phenomena across multiple domains [10]. This methodology facilitates high-fidelity simulation of physical systems, utilizing both built-in and custom components to accurately replicate real-world conditions. However, despite its prowess in physical system modeling, Simscape originally provided fault injection features only for its electrical domain, posing challenges for conducting comprehensive fault analyses within Simscape models.

Our work addresses this limitation by introducing custom fault injection blocks within the Simscape environment. By exploiting Simscape's robust component customization capabilities, we have developed blocks that can be programmatically manipulated to simulate a wide range of fault scenarios. Addressing this gap, our work pioneers the development of fault injection blocks within the Simscape environment. Leveraging Simscape's powerful component definition capabilities, we have created custom blocks that can be programmatically enabled and disabled, allowing for detailed and controlled simulation of fault scenarios. This approach enables the comprehensive analysis of the model under various fault conditions but also sets a precedent for extending fault injection capabilities to Simscape models.

C. Multi-domain fault injection

A cyber-physical system, like an airplane, comprises multiple physical domains. In such a system, the electrical, mechanical, hydraulic, and thermal domains are present. According to the physical properties that characterize each system component, there are connections between these physical domains. For example, in an electromechanical system composed of purely mechanical and electrical components, a particular behavior or condition within one of the two physical domains affects the other. In this context, a faulty component belonging to a specific domain could also have consequences for nearby components belonging to different domains. For this reason, it is critical to carry out a fault injection campaign that covers all physical domains of interest for system security. However, accomplishing this is not always trivial, as the various physical domains have different simulation techniques and fault models.

In a previous paper [11], the authors present a methodology to create a taxonomy of mechanical faults that could suit multiple mechanical systems. Specifically, the authors exploit physical analogies between the electrical and mechanical domains to create analytical mechanical fault models [12]. These fault models are then injected at the differential equation level to create and simulate system fault behaviors. Simulations of these faulty model versions support functional safety analysis at the system level. The language used to model and simulate the example systems is Verilog-AMS, but the approach is replicable in other programming environments if the system is modeled through differential equations. For instance, SystemC-AMS is another valid candidate for modeling Cyber-Physical Systems (CPSs) [13]. The advantage of the analytical fault models presented in the article is versatility depending on the reference system: multiple mechanical failures at the physical level can be modeled through the same fault models at the mathematical level. For this reason, the faults presented are suitable for a wide range of mechanical components. The article shows some possible physical-level effects of the fault models presented.

III. METHODOLOGY

This methodology outlines a general approach for fault injection and synthetic data generation applicable to various critical aviation components. While the specific example used here focuses on LGS, the core steps can be adapted to other aviation systems by replacing component-specific details. The general flow of this methodology is shown in Figure 2.

A. Select critical component

As depicted in Figure 2, the first step involves selecting the critical component within the chosen aviation system for fault injection analysis. This selection can be based on factors like:

- **Safety Significance**: Components crucial for the aircraft's safe operation are given priority. Ensuring the reliability of these components is paramount to overall aviation safety.
- **Historical Failure Data**: Components with a higher frequency of reported failures should become prime candidates.
- **Availability of High-Fidelity Models**: The selection process is also influenced by the existence of high-fidelity models or the feasibility of developing such models for the component in question. High-fidelity models are essential for accurately simulating the component's behavior under normal and fault conditions, thereby ensuring the effectiveness of the fault injection analysis.

B. Gathering failure reports

A critical step in our methodology is conducting a thorough literature analysis of potential failure modes associated with

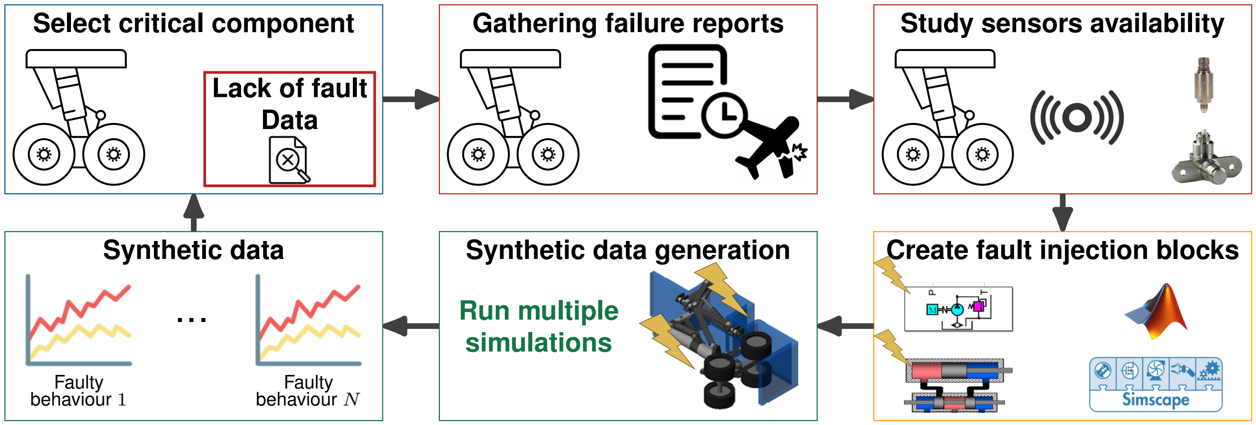

Figure 2: Overview of the methodology for fault injection and synthetic data generation, with an example of a LGS. This approach encompasses critical component selection, literature analysis, sensor capability assessment, development of custom fault injection blocks, and synthetic data generation.

the selected critical aviation component. This analysis is essential not only for engineers specializing in simulations who might not have extensive mechanical experience but also for more experienced technicians accustomed to hands-on work with these systems. By reviewing a wide range of data sources, including industry reports [14]–[17], academic publications, and incident databases [18], [19], professionals across the spectrum can deepen their understanding of component behaviors and failure mechanisms. This comprehensive literature analysis empowers engineers and technicians alike to expand their knowledge base, enabling them to anticipate and simulate a broader range of failure scenarios. For engineers, it enhances their ability to create more accurate and comprehensive simulation models. For technicians, it provides a broader perspective on potential failure modes, enriching their practical experience with a deeper theoretical understanding. Ultimately, this approach fosters a more holistic understanding of aviation systems' vulnerabilities.

C. Study sensors availability

This phase of our methodology is devoted to examining the sensors equipped with the critical component, focusing on the types of data they collect. Understanding sensor capabilities and the data they provide is crucial for configuring our simulations to accurately mirror the system's behavior and performance under various fault conditions. It is essential to recognize that in a real-world scenario, components are not equipped with an unlimited number of sensors due to constraints such as cost, space, and practicality. Therefore, simulations strive to emulate these real-world limitations, ensuring that the sensor distribution within the simulation closely reflects what would be feasible on the actual component.

D. Create fault injection blocks

This step details the development of custom blocks within the chosen simulation environment (e.g. Simscape) to inject various faults into the model. These blocks aim to replicate the identified failure scenarios and enable a comprehensive analysis of the system's behavior under fault conditions. Leverage the simulation environment's capability to define custom components with functionalities tailored for fault injection. These blocks should be:

- **Parameterizable**: Allowing for customization of fault severity levels, providing flexibility in simulating various fault conditions from mild to severe.
- **Mathematically Represented**: Utilizing equations to simulate the desired fault behavior. Each block utilizes mathematical equations to simulate the specific behaviors associated with each fault accurately, ensuring the simulation outcomes closely mirror real-world phenomena.
- **Easily Enabled/Disabled**: These custom blocks should be designed for easy enabling and disabling, preserving the integrity and readability of the original model. This capability maintains the system model's clarity by allowing users to quickly switch between the default and fault-injected states without modifying the model's fundamental structure.

E. Synthetic data generation

The final phase of this methodology involves generating synthetic data through fault injection experiments. This process involves executing simulations incorporating various fault conditions to assess the system's response. The data collected from these simulations serves as a foundation for subsequent analysis and model validation.

IV. Model Evaluation

This section demonstrates the application of our proposed methodology to LGS model, illustrating its practical implementation and effectiveness.

A. Choice of the critical component

Figure 3 depicts the case study we chose; it is a LGS model that uses Simulink for control logic and Simscape for the mechanical and hydraulic subsystems. Beyond producing traditional data outputs like scope views and waveform plots,

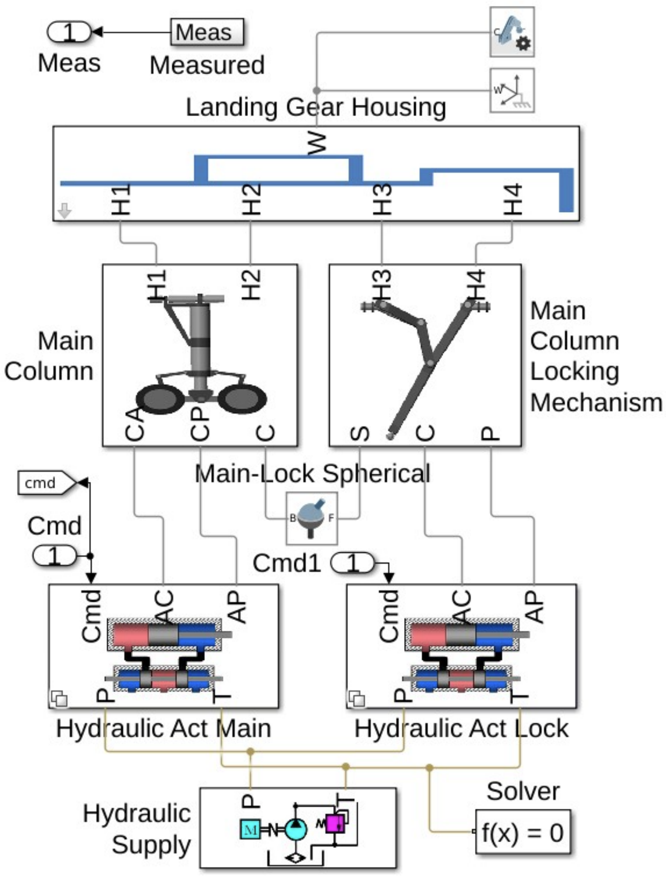

Figure 3: Close-up view of the Simscape model representing the LGS [20]. Each block within the model represents a specific component or subsystem. These blocks can be further decomposed into sub-blocks, which mathematically describe the behavior of individual mechanisms using equations.

our simulation enhances comprehension through animated visualizations of the landing gear mechanics. This feature provides an intuitive understanding of deployment, locking, retraction, and unlocking sequences. This model is particularly valuable for its multidomain approach, accurately reflecting the integration of control, mechanical, and hydraulic systems within a single simulation environment. The simulation incorporates animation beyond static analysis, offering dynamic insights into the system's operational behavior. Such a multidomain and visually enriched simulation approach aligns with state-of-the-art aviation systems, offering a nuanced case study that bridges theoretical analysis with practical, real-world operational dynamics.

B. Gathering failure reports

To understand the fault landscape for effective synthetic data generation, our literature review targets hydraulic landing gear components, pinpointing the most common failure modes identified over the past century. This focused investigation draws from the following:

- **Industry Reports**: Aviation safety organization reports analyze trends in landing gear incidents, highlighting frequent failure modes like actuator leaks and pipeline wear [14]–[17].
- **Academia Articles**: Academic publications on LGS provide valuable information on the actual state-of-the-art in the academic research world regarding the simulations and the practices adopted to study these mechanisms [20]–[22].
- **Incident Databases**: Aviation incident databases like The Aviation Herald [19] and Aviation Safety Network [18] provide real-world insights into landing gear malfunctions and root causes, with The Aviation Herald established in 2008 and recognized for its independence. The Aviation Safety Network has operated under the Flight Safety Foundation since 1945.

Our targeted literature review culminates in identifying the most recurrent faults documented through extensive research and analyses. The following faults were consistently highlighted as prevalent issues:

1) **Oil straining**: The obstruction of oil flow due to contaminants leads to reduced hydraulic efficiency.
2) **Oil filter blocked**: The clogging of oil filters hampers the cleanliness of the hydraulic fluid, affecting system performance.
3) **Pipeline leakage**: The deterioration of hydraulic lines over time can lead to leaks and reduced system pressure.
4) **Actuator external leakage**: The loss of hydraulic fluid from actuators when the hydraulic fluid flows from the system to the outside environment.
5) **Actuator internal leakage**: The loss of hydraulic fluid from actuators due to damage to actuator seals, which close the gap between the actuator piston and the cylinder wall.
6) **Stuck reversing valve core**: The malfunctioning of valves that control hydraulic flow direction, hindering the system's operation.
7) **Oil contains wear particles**: Metallic particles in the oil can wear down hydraulic components and reduce system life.
8) **Oil mixed with air**: Air entrapment within the hydraulic fluid leads to inefficiencies and potential system failure.

C. Sensors availability

After the cataloging phase, it is imperative to determine which onboard sensors are available to monitor these specific faults. This step is crucial for acquiring pertinent data that reflects the system's operational state and performance while in service. Based on common sensors found in LGS, the following parameters can typically be tracked:

- **Proximity**: These sensors are typically mounted on actuators and wheels. Proximity sensors detect the extension and retraction positions on actuators, providing binary or continuous positional data. Regarding wheels, they can measure the weight on wheels, indicating whether the aircraft is airborne or on the ground, which is critical for ensuring the correct timing of landing gear operations.

- **Pressure**: Such sensors monitor the hydraulic system's pressure levels, offering insights into the state of the entire aircraft's hydraulic support. Pressure sensors play a crucial role in detecting leaks, blockages, or failures in the hydraulic system that could impact the deployment or retraction of the landing gear.

While these types of sensors can be found almost on every LGS, the quantity and quality of the sensors, and consequently the data they provide, can vary significantly between different aircraft models and manufacturers.

D. Fault injection custom blocks

We have developed custom blocks designed to simulate various fault scenarios to advance the fault injection capabilities for the LGS model within Simscape. These blocks replicate the operational conditions under which faults like actuator friction and hydraulic supply limitations can impact the system's performance. Through the Simscape language, these custom components are detailed to capture the dynamics of faults using a foundation of mathematical equations and physical connections.

1) Actuator Friction Block: This block builds upon the translational friction model [23], extending its functionality to simulate the friction experienced by actuators. The model incorporates Stribeck, Coulomb, and viscous friction components to replicate the frictional forces accurately. These forces are crucial for understanding how friction can affect the deployment and retraction of the landing gear, especially under varying operational conditions. Adding a programmable parameter allows this block to be enabled or disabled, offering flexibility in simulating and analyzing the effects of actuator friction dynamically during the simulation runs.

$$\begin{aligned} F =& \sqrt{2e} \cdot (F_{brk} - F_C) \cdot \exp\left(-\left(\frac{v}{v_{st}}\right)^2\right) \cdot \frac{v}{v_{st}} \\ &+ F_C \cdot \tanh\left(\frac{v}{v_{Coul}}\right) + f_v \end{aligned} \tag{1}$$

The total friction force F is a composite of:

- F_C represents Coulomb friction;
- F_{brk} represents breakaway friction;
- v_{brk} is the velocity at which breakaway; friction transitions to dynamic friction;
- v_{St} defines the Stribeck velocity threshold;
- v_{Coul} is the Coulomb velocity threshold;
- f denotes the viscous friction coefficient.

2) Hydraulic Supply Fault Block: Similarly, the Hydraulic Supply Fault block is designed to simulate restrictions in the hydraulic system, such as those caused by partial blockages or component wear. This block utilizes a Rotational friction approach to represent the hydraulic resistance and its impact on the system's efficiency [24]. By integrating this block into the hydraulic supply system of the LGS model, we can explore the consequences of diminished hydraulic pressure and flow on landing gear operation.

$$\begin{aligned} T =& \sqrt{2e} \cdot (T_{brk} - T_C) \cdot \exp\left(-\left(\frac{w}{w_{st}}\right)^2\right) \cdot \frac{w}{w_{st}} \\ &+ T_C \cdot \tanh\left(\frac{w}{w_{Coul}}\right) + f_w \end{aligned} \tag{2}$$

The total friction torque T is a composite of:

- T_C represents Coulomb friction torque;
- T_{brk} is breakaway friction torque;
- w_{brk} is breakaway friction velocity;
- w_{St} is Stribeck velocity threshold;
- w_{Coul} is Coulomb velocity threshold;
- w is relative velocity;
- f represents the coefficient of viscous friction.

By implementing these custom fault injection blocks, our study pioneers a methodical approach to assessing the LGS's resilience and vulnerabilities under various simulated fault conditions. This development represents a significant step forward in utilizing Simscape for detailed fault analysis and underscores the potential of custom blocks in enriching simulations.

E. Synthetic data generation

With the fault blocks in place, we move on to synthetic data generation. This step involves running multiple simulations at different severity levels for the injected faults. The resulting synthetic data serves two purposes: analyzing the system's behavior under various fault conditions and training robust PHM algorithms for predictive maintenance.

The LGS model was subjected to simulations under three conditions:

- **Healthy**: This baseline scenario represented the system functioning normally, without any faults.
- **Hydraulic Supply Fault**: The corresponding fault block within the model was activated to simulate the hydraulic supply malfunction.
- **Actuator Friction Fault**: The dedicated fault block for actuator friction was enabled within the model.

For each fault scenario, simulations were run with varying parameters to explore a range of potential fault severities. In the absence of empirical data from real-world systems or literature, specific parameter values were selected to highlight the abnormal behavior of different failure modes and severities on the LGS:

- For the **Actuator Friction Fault**, we applied the fault block across both actuators, using parameters that capture a broad range of friction-induced behaviors. These included a breakaway friction of $10\,000\,\mathrm{N}$, a breakaway friction velocity of $0.1\,\mathrm{m/s}$, a coulomb friction force of $20\,\mathrm{N}$, and a viscous friction coefficient of $100\,\mathrm{N \cdot s/m}$. This set of parameters was selected to demonstrate the fault's impact on actuator performance, specifically highlighting how friction can significantly affect the actuator's ability to retract and extend under various conditions.

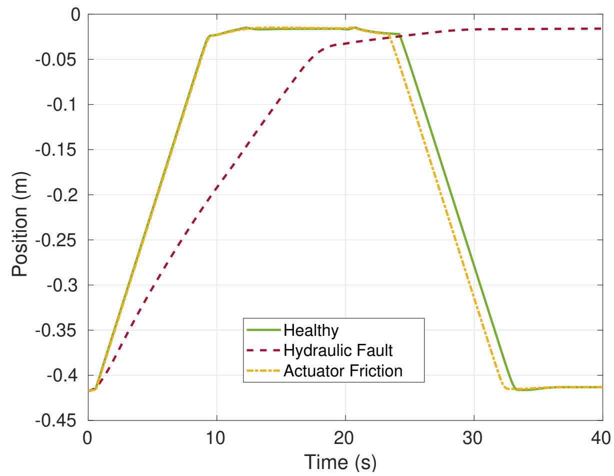

Figure 4: Position of the Main Actuator.

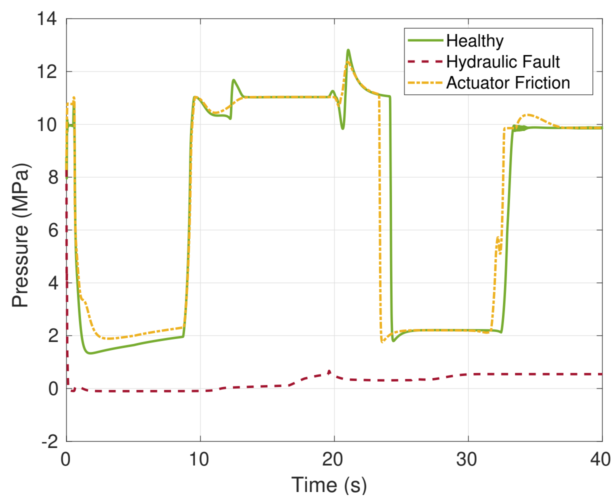

Figure 5: Pressure of the Main Actuator.

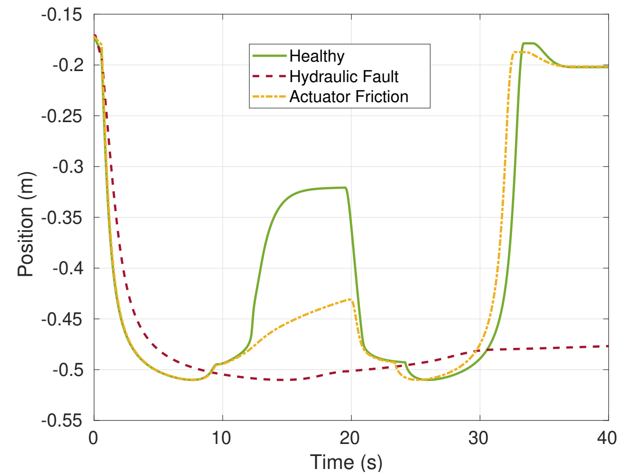

Figure 6: Position of the Lock Actuator.

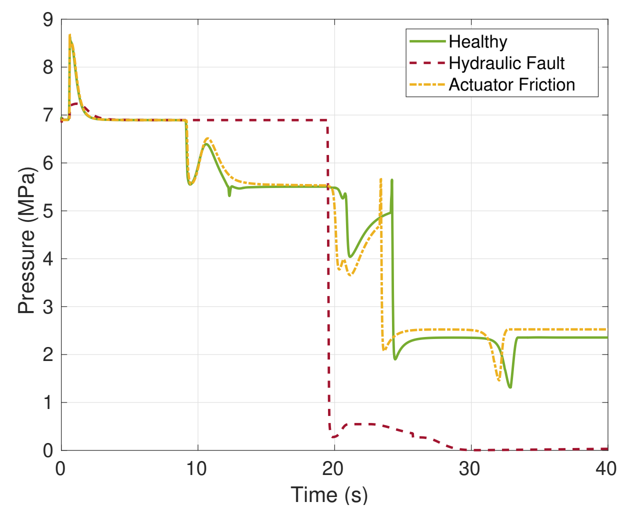

Figure 7: Pressure of the Lock Actuator.

- For the **Hydraulic Supply Fault**, the parameters we chose are a breakaway friction torque of $1.5\,\mathrm{N}\cdot\mathrm{m}$, a breakaway friction velocity of $0.1\,\mathrm{rad/s}$, a Coulomb friction torque of $1.5\,\mathrm{N}\cdot\mathrm{m}$, and a viscous friction coefficient of $0.001\,\mathrm{N}\cdot\mathrm{m}\cdot\mathrm{s/rad}$.

Figures 4 and 5 illustrate the different effects of these faults on the main actuator's position and pressure, respectively, revealing critical insights into these specific fault types. For instance, actuator friction introduces a delay in retraction, which is attributed to pressure variations. Meanwhile, a hydraulic supply fault leads to a significant deployment delay and a failure to retract, underpinning a total pressure loss. Figures 6 and 7 extend this analysis to the lock actuator, showcasing similar fault impacts and underscoring the comprehensive nature of these failure modes on LGS integrity. The selection of these two fault scenarios (hydraulic supply and actuator friction) aimed to encompass a broad spectrum of potential LGS failure at a functional level. Although these fault blocks are distinct, they can be traced back to similar failure causes, albeit in different positions within the system. While further investigation into specific failure modes is warranted, these initial experiments provide valuable insights into the model's ability to capture critical system behaviors under fault conditions. Table I shows the relationship between the fault blocks and the possible cause.

Table I: Simulated failure blocks and fault cause.

Failure block	Failure cause
Actuator friction	1,4,5
Hydraulic supply fault	2,3,6,7,8

V. Discussion

Our simulations targeted two critical fault conditions within the LGS hydraulic supply malfunction and actuator friction. These conditions represent a broad spectrum of potential LGS failures at a functional level. The analysis revealed distinct impacts on both main and lock actuators, aligning with expectations. Hydraulic supply faults caused significant deployment delays and prevented retraction, while actuator friction primarily introduced delays during retraction. These observations were supported by the pressure variations observed in the simulations. Moreover, the selection of representative cases prioritized faults with a high impact on system functionality and real-world relevance to LGS operations. These outcomes demonstrate the feasibility of the methodology for analyzing critical system behaviors under fault conditions and suggest that our simulation parameters effectively captured the dynamics of these fault conditions. By simulating various fault scenarios, designers can identify potential weaknesses and incorporate features that mitigate their impact. Additionally, the model can also be used to develop training programs for maintenance personnel and inform the development of robust PHM algorithms that leverage synthetic data to continuously monitor the LGS for signs of faults and enable predictive maintenance.

It is becoming increasingly recognized among vendors that simulations incorporating fault scenarios can offer significant value, yet this is a nascent field requiring further research. Current simulation tools often lack the capabilities to easily incorporate and simulate faults, representing a significant barrier to widespread adoption and implementation. Addressing these gaps is crucial for advancing the field and fully realizing the potential of fault simulations.

In aviation, model-based design in aviation is a well-established practice, and access to high-fidelity models is crucial. However, researchers often face limitations in acquiring such models. Future work can delve deeper into specific failure modes and expand the fault library to encompass a more comprehensive representation of potential LGS issues. Real-world LGS health data can be used to further refine and validate the model in an iterative process, enhancing its accuracy and effectiveness. It is essential to acknowledge that the value of synthetic data generated by a model depends heavily on its quality. Effective LGS modeling requires a high level of expertise, but this expertise exists within the aircraft domain, where high standards are necessary.

VI. Conclusion

This study presented a comprehensive methodology for simulating and analyzing various fault scenarios exemplified through a detailed study of a Landing Gear System (LGS) model. We evaluated how specific faults (hydraulic supply malfunctions and actuator friction) impact system functionality. The simulations captured a broad spectrum of potential LGS failures at a functional level. The analysis revealed distinct impacts on main and lock actuators, aligning with expectations. These findings demonstrate the validity of the proposed methodology and the custom fault injection blocks developed for this purpose. This analytical ability offers valuable insights for several Prognostic and Health Management (PHM) algorithms. Furthermore, generating synthetic data across diverse fault scenarios establishes a solid foundation for creating and refining robust PHM algorithms, enhancing predictive maintenance strategies.

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