The Future of Aircraft Maintenance: Goals and Challenges of Digital Twins for In-flight Operations

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Abstract

The aviation sector is rapidly advancing towards the next generation of aircraft, expected by 2035, propelled by Artificial Intelligence (AI), cloud computing, and cybersecurity technologies. The Digital Twin is at the forefront of these advancements as it aims to integrate all these technologies. However, significant challenges arise in implementing Digital Twins, particularly for in-service aircraft with limited computational resources. This research aims to develop a power-efficient Digital Twin framework tailored for predictive maintenance. After an extensive review of the latest Digital Twin research, considerable effort was focused on creating a high-fidelity model of a critical aircraft component. Based on this model, a methodology for fault data simulation has been developed. The simulated data, generated through fault injection in a multi-physics model, will be the foundation for designing an effective machine-learning algorithm for predictive maintenance. Finally, the algorithm will be deployed on a device with limited computational resources without compromising the system's reliability.

Keywords

Digital Twin, Predictive Maintenance, Aircraft

1. Introduction

Digital Twins are increasingly gaining traction across various industries, notably in the aerospace sector [1]. A Digital Twin (see Figure 1) is a virtual representation that accurately mirrors a physical system, be it natural, engineered, or social. This model is continuously updated with real-time data from its physical counterpart, enabling it to predict outcomes and support decision-making processes that enhance value. A key feature of a Digital Twin is the two-way interaction between the virtual model and its physical version [2]. The advantages of utilizing Digital Twins in aerospace applications are numerous, including shortened design cycles and lower maintenance costs compared to traditional modeling and simulation approaches [3]. In particular, the maintenance aspect is one of the most important due to the extremely long period of the aerospace product life cycle.

Currently, the industry relies mainly on time-based maintenance protocols, scheduling maintenance at fixed intervals regardless of the actual condition of the aircraft components. While systematic, this method often results in either excessive maintenance, which is costly, or insufficient maintenance, which can compromise safety. In 2022, airlines worldwide spent about $76.8 billion on maintenance, repairs, and overhauls, accounting for 10.9% of their total operational costs [4]. Consequently, the aviation industry is on the brink of a major shift due to advancements in condition-based and predictive maintenance methods [5]. In fact, the Advisory Council for Aeronautics Research in Europe (ACARE) envisions that by 2035, condition-based maintenance will become the standard practice [6]. To reach these goals, Digital Twins will be a major player in this transition.

Based on these developments, this research aims to address the challenges associated with implementing Digital Twin technology for predictive maintenance in aerospace. The following sections will introduce the open problems and detail how this research seeks to resolve them.

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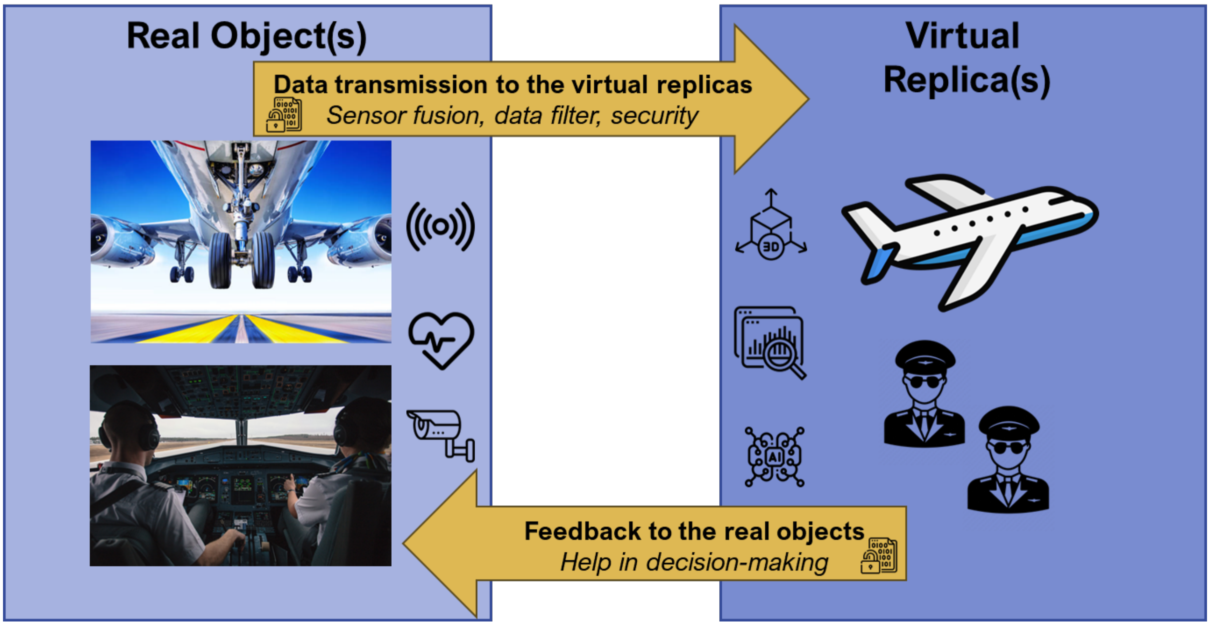

Figure 1: Illustration of the Digital Twin concept. The virtual representation continuously updates with data from the real object and provides feedback for decision-making. The inclusion of both a Cyber-Physical System and a human underscores the imperative to consider human factors in the decision-making process.

2. Open challenges

Despite the significant potential of this technology discussed in the previous section, Digital Twin is still largely unexplored, and many challenges must be addressed:

- **Lack of formal definition of Digital Twin**: At the time of writing, many different definitions of Digital Twins existed; however, there was no standardized methodology to effectively create a Digital Twin for predictive maintenance in the aircraft domain. The lack of consensus complicates the development and deployment of Digital Twin technologies, leading to variations in implementation, functionality, and expectations. A standardized definition and framework are essential for ensuring interoperability and consistency across different systems and applications [2].
- **Models and Data Availability**: A significant challenge is the scarcity of publicly available models and datasets due to proprietary restrictions, which limits research advancements. In the aerospace sector, data related to aircraft operations, maintenance records, and performance metrics are often considered sensitive and not readily shared. The lack of access hinders researchers and developers from building, validating, and improving Digital Twin models. Additionally, the absence of standardized models obstructs benchmarking and comparative analysis, which are essential for technological progress [7].
- **Data Imbalance and Quality**: Available datasets used to train and benchmark the proposed machine learning models are commonly imbalanced and skewed towards normal operations with insufficient failure data. Thus, affects the model's ability to learn from and predict rare failure events. Most datasets heavily favor normal operational data, while failure or anomalous data points are scarce. The data imbalance can lead to biased models that perform well under normal conditions but fail to accurately predict or detect failures, thereby undermining the reliability and effectiveness of predictive maintenance strategies [7].
- **Explainability and Uncertainty Quantification**: The increased use of artificial intelligence and empirical modeling in engineering highlights two significant issues. First, there is no standardized method for reporting on model verification, validation, and uncertainty quantification [2]. The absence of standardized procedures makes it difficult to assess the reliability and robustness of models, leading to potential risks in critical applications. Second, there is often a lack of focus

on how confident we can be in the results these models produce. Explainability in AI models is crucial for gaining trust from stakeholders, particularly in high-stakes industries like aerospace. Without clear explanations and quantifiable measures of uncertainty, it is challenging to interpret the results and make informed decisions based on model outputs.

3. Evolution and Future Directions of Digital Twin Approaches

The aforementioned challenges are at the base of the two primary approaches for building Digital Twins: the model-driven approach and the data-driven approach [3, 8]. Both have their strengths and weaknesses, and recent trends aim to combine these approaches into a hybrid model to leverage their respective advantages.

3.1. Model-Driven approach

The model-driven approach, also known as the physics-based approach, relies on creating detailed mathematical models based on the fundamental physical principles governing the system. These models are developed using domain knowledge and are typically derived from first-principle equations, empirical relationships, and high-fidelity simulations. One of the significant strengths of the model-driven approach is its high interpretability; the mathematical equations and relationships used in the model are based on well-understood physical laws, making the results easy to interpret and validate. Furthermore, these models possess strong predictive power as they can forecast the system's behavior under various conditions, including those not directly observed in the data. The consistency and stability of model-driven approaches are also noteworthy, as they are generally stable and consistent across different scenarios due to their basis in physical principles. However, the model-driven approach is not without its drawbacks. Developing accurate physics-based models can be time-consuming and costly, requiring significant expertise and computational resources. These models often lack flexibility and struggle to adapt to new data or unforeseen conditions that were not included in the original equations. Additionally, scalability issues can arise as the complexity of the system increases, rendering the models extremely complex and computationally intensive [9].

3.2. Data-Driven approach

The data-driven approach leverages large datasets and advanced statistical methods, such as machine learning, to build models that learn patterns and relationships directly from the data without relying heavily on prior domain knowledge. The proposed approach is highly adaptable, with models that can quickly adjust to new data and mutable conditions. The efficiency of data-driven methods allows for relatively quick development and deployment, provided there is sufficient data and computational power. Furthermore, these methods can handle large-scale data and complex systems, making them suitable for applications involving big data. Nevertheless, data-driven models have their limitations. Many of these models, particularly those based on deep learning, can act as "black boxes," providing little insight into how decisions are made. The accuracy and reliability of data-driven models heavily depend on the quality and representativeness of the training data, meaning that imbalanced or noisy data can significantly impair model performance. Additionally, without careful management, data-driven models can overfit the training data, leading to poor generalization of new or unseen data.

3.3. Hybrid approach

Given the complementary strengths and weaknesses of model-driven and data-driven approaches, a hybrid approach seeks to integrate both methodologies to create more robust and versatile Digital Twins. By incorporating physical principles and data-driven capabilities prediction, hybrid models can offer better interpretability than purely data-driven models. The integration allows the model to

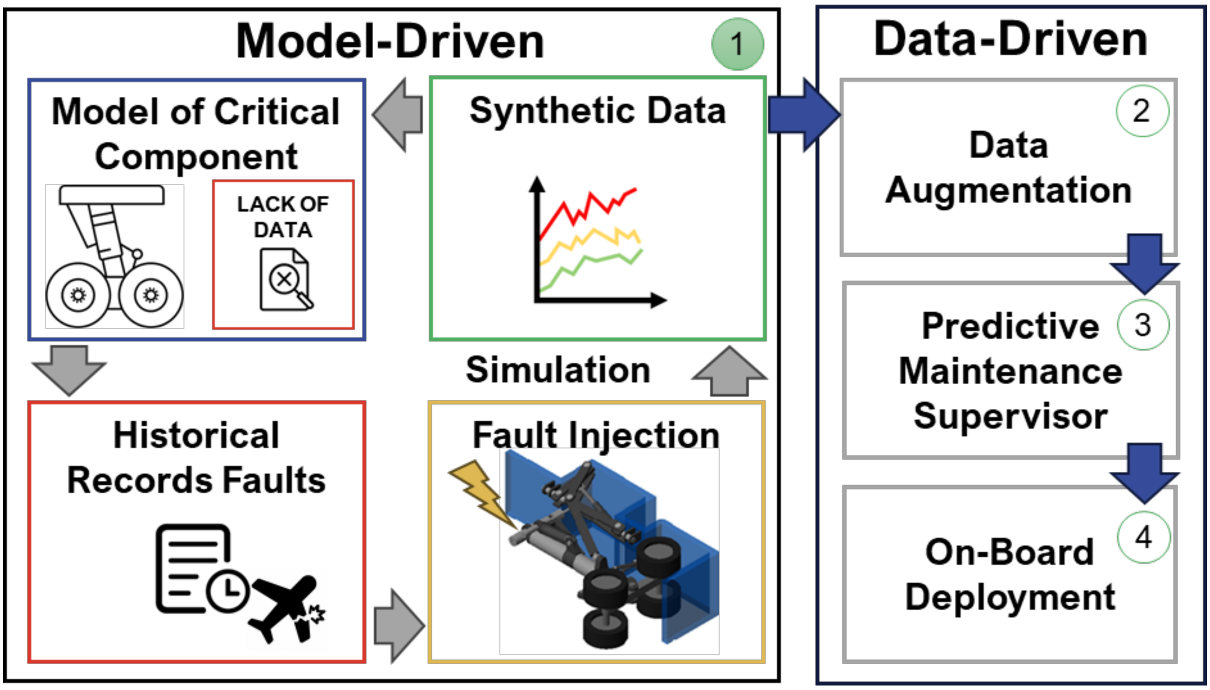

Figure 2: An overview of the proposed hybrid framework for implementing and deploying an In-flight Digital Twin for predictive maintenance. The proposed framework wants to exploit the benefit of the two main approaches to building Digital Twins. The numbers represent the different steps described in section 4.

leverage the adaptability of data-driven methods while maintaining the consistency and stability of physics-based models.

4. Possible Solution

Starting from these open challenges and approaches described in the previous sections, the paper wants to tackle these challenges by developing a hybrid Digital Twin framework (see Figure 2) delineated as follows:

1. **Design a high-fidelity model and robust methodology for faulty data simulation**: The first step involves creating a detailed model of a critical aircraft component to simulate various fault conditions. The objective is twofold: firstly, to align with the current trends in the aerospace industry for designing and validating aircraft systems, and secondly, to enhance existing fault simulation methodologies. The high-fidelity model will replicate real-world conditions as closely as possible, ensuring that the simulated data accurately reflects potential faults and their impact on the system.
2. **Develop a tool for data augmentation**: The step focuses on using data augmentation techniques to improve the quality of the dataset. The goal is to make these enhanced techniques accessible to engineers who possess strong domain expertise but have limited knowledge of artificial intelligence. By doing so, we aim to bridge the gap between domain experts and AI, enabling more effective utilization of AI-driven insights in the design and maintenance processes. Based on the distribution of the model-based data, the tool will generate diverse and representative data that can improve the training and validation of predictive maintenance models.
3. **Develop and evaluate a predictive maintenance supervisor**: The step focuses on designing a predictive maintenance supervisor using state-of-the-art machine learning algorithms. The supervisor will monitor the health of the aircraft systems in real-time, predicting potential failures before they occur [10]. The focus will be on the explainability and reliability of the proposed solution, ensuring that the algorithms provide transparent and understandable results that can be

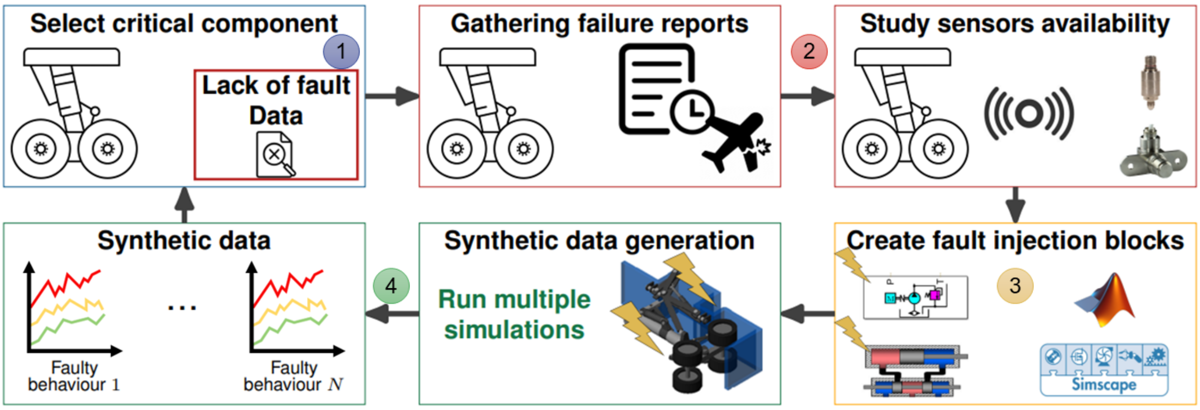

Figure 3: Close-up view of the model-driven methodology for fault injection and synthetic data generation applied to a landing gear system. The framework encompasses critical component selection, literature analysis, sensor capability assessment, development of custom fault injection blocks, and synthetic data generation.

trusted by pilots during the flight and by the maintenance personnel. Rigorous evaluation will be conducted to validate the accuracy and effectiveness of the supervisor in predicting faults.

4. **Deployment on hardware with limited computational power**: Finally, the proposed solution will be optimized for deployment on hardware with limited computational resources, typically found in flight operations. The optimization process will aim to minimize space and resource requirements without compromising efficiency and reliability. In this way, the predictive maintenance system can operate effectively within the constraints of the aircraft's onboard systems, providing real-time insights and alerts without overwhelming the available computational capacity.

By using this hybrid framework, we can leverage the decades-long experience of the aeronautical industry with model-driven design and high-fidelity software tools such as CATIA, ANSYS, Autodesk, and Simulink. The integration will facilitate the generation of analytically created and deterministic fault data. Consequently, this deterministic faulty and healthy data will serve as a foundation for generating additional data through Generative AI, thereby enhancing the overall quality and reliability of the synthetic datasets. The proposed approach wants to address the current limitations posed by the scarcity of data, allowing traditional machine-learning techniques to perform better than deep-learning techniques [7]. Additionally, this framework's reliance on well-established and widely used technologies and instruments will guarantee its usability and seamless integration into existing workflows in the avionics field.

5. Preliminary results

Our preliminary work has focused on validating system failure modes through fault simulation as a foundational step toward developing an effective Digital Twin framework for predictive maintenance. Fault simulation has recently gained attention for its potential to enhance predictive maintenance strategies. However, the field is still in its early stages, and comprehensive fault libraries and standardized methodologies are not yet fully developed. A generic methodology (see Figure 3), applicable to different aircraft parts, has been proposed [11]:

1. **Critical Component Selection**: The first step involved selecting a critical component. We selected the landing gear system, a crucial component that ensures aircraft safety during the essential takeoff and landing phases. Despite the weight and initial aircraft cost of the landing gear system, it contributes to 20% of the airframe's direct maintenance costs.
2. **Failure Data Gathering**: After identifying the critical component, we gathered data on common failure modes by reviewing the literature. Additionally, we identified the sensors available on the

system to monitor its health.

3. **Development of Fault Blocks**: Given the early state of fault simulation research, we developed specialized fault blocks within Simscape to simulate conditions such as actuator leaks, pipeline wear, and hydraulic supply issues.
4. **Data Collection and Analysis**: Consequently, we collected extensive data through these simulations, meticulously analyzing it to identify patterns and correlations in system behavior under different fault conditions. Our analysis indicated that the framework could effectively simulate fault conditions across multiple domains—mechanical, hydraulic, and control systems—providing a comprehensive understanding of the system's behavior under fault conditions.

The initial results from these models demonstrated promising accuracy and reliability, suggesting their potential application in real-world scenarios. The fault simulation framework successfully replicated various failure modes, offering valuable insights into the system's resilience and identifying potential areas for improvement. It is important to note that the proposed methodology tightly depends on the quality of the model, and developing such high-fidelity models can be a costly and lengthy process. However, the expertise required to develop these models is well-established in the aerospace industry.

6. Future works

Based on the work presented in the previous section, our future work will mainly focus on the Data-driven part of the framework:

1. **Enhancing Data Quality and Generating Explainable and Reliable Data**: The first step will involve generating explainable and reliable data. We will develop a pipeline that engineers with limited AI knowledge but strong domain expertise can easily use, bridging the gap between model-driven and data-driven approaches. Diffusion models, a type of Generative AI, will be employed to create synthetic datasets that augment the existing data. These models are particularly effective in generating high-fidelity data that can simulate a wide range of fault conditions, thereby addressing the scarcity of failure data, which hampers traditional machine learning models.
2. **Creating an Explainable Predictive Maintenance Algorithm**: Subsequent efforts will focus on creating an explainable predictive maintenance algorithm to monitor the health state. Explainable AI techniques will be integrated to show the transparency and interpretability of the machine learning models used. The model's explainability is crucial for gaining the trust of pilots, maintenance engineers, and regulatory bodies, as it allows for a clear understanding of how predictions are made and facilitates better decision-making processes. Moreover, if the algorithm is not performing well, the explainability will make it easier to identify which part of the model is incorrect, allowing for targeted adjustments and improvements to the predictive maintenance supervisor.
3. **On-Board Deployment with Limited Computational Capabilities**: Finally, we will deploy the proposed solution on hardware with limited computational capabilities. We will explore edge and split computing techniques to minimize space and energy requirements during in-flight operations.

For scenarios where the solution needs to operate locally without in-flight connectivity, data gathered during flight can be securely transferred using a secure transfer protocol at the end of the mission [12]. Ensuring robust security against potential threats is essential to maintaining the integrity and confidentiality of the data and allowing the system to be updated after every mission. By tackling the numerous challenges associated with Digital Twin implementation, including data scarcity, model interpretability, and deployment constraints, this framework offers a robust and comprehensive approach. The integration of advanced AI techniques and high-fidelity simulations promises to significantly enhance predictive maintenance capabilities, ultimately leading to more reliable, efficient, and sustainable operations within the aerospace industry. The potential positive outcomes far outweigh the challenges, marking a transformative step forward for Digital Twin technology.

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