Aircraft Structures Life-cycle Simulation through Digital Twins and Model Updating Techniques

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Abstract. Numerical modeling tools have become essential in the realm of aircraft structural design and assessment. These tools allow for the analysis of intricate structural parts, incorporating diverse material properties and loading scenarios while minimizing the need for extensive experimental testing. However, the current models face limitations in accurately capturing the nuanced real-world behavior of aircraft structures. Challenges arise due to factors such as material property scatter, manufacturing-induced geometric deviations and residual stress, and other effects that can only be estimated or fully captured during service.

This work aims to evaluate and discuss the potential impact of digital twins on addressing these limitations and enhancing the reliability of numerical models through model updating techniques. Digital twins, virtual replicas of physical assets or systems, can improve the solutions to overcome the gaps between numerical models and real-world behavior. By integrating and processing data from sensors, operational inputs and historical data, digital twins provide a more comprehensive understanding of the structural behavior throughout an aircraft's life cycle. With the exploitation of machine learning techniques, new methods for model calibration and validation are possible, combining experimental inputs with simulation models. By leveraging these techniques, digital twins can be continuously updated and refined, allowing for more accurate predictions of structural behavior and performance.

These models can enable real-time monitoring and more precise damage assessment, supporting the decision making in diverse contexts. In addition, integrating sensor data and model updating techniques, digital twins have the potential to improve the design and maintenance operations. They can provide valuable insights into the structural health, safety, and reliability of aircraft structures, leading to more efficient and safer operations.

Keywords: Digital-twins, Finite Element Models, Damage Tolerant Design, Structural Design, Model updating

1 Introduction

In the rapidly evolving aerospace industry, the design, analysis, and maintenance of aircraft structures have always been of paramount importance to ensure the safety, lightweight, and longevity of these safety critical systems, Liu et al. [1]. As aircraft continue to push the boundaries of technological advancements, the need for accurate and reliable predictive tools becomes increasingly critical. The integration of artificial intelligence (AI) and machine learning has further revolutionized aircraft design, offering capabilities ranging from automated generative design to rapid data analysis for identifying optimization opportunities, Oroumieh et al. [2] and Min et al. [3].

In recent years, the integration of digital twin technology and model updating techniques has emerged as a revolutionary approach, promising to revolutionize how the life-cycle simulation of aircraft structures is conducted, Tuegel [4]. A common definition of a digital twin is a virtual representation of a physical asset, process, or system, built upon the real-time integration of data from sensors, simulations, and other sources, Jones et al. [5]. This innovative technology, when applied to aircraft structures, allows engineers and decision makers to monitor and analyze the structural behavior comprehensively and continuously throughout their entire life cycle, Hochhalter et al. [6]. This concept was discussed in detail for the aeronautical sector in a position paper promoted by American Institute of Aeronautics and Astronautics (AIAA) and by Aerospace Industries Association (AIA), Arthur et al. [7]. The main idea for the digital-twin is presented in Figure 1. Diverse applications of digital twins could be exploited, comprising failure analysis, performance validation, design optimization, among many others. The ability of the digital twins to replicate the behavior and performance of physical aircraft, digital twins offer a powerful means of understanding structural responses under various operational and environmental conditions, which can significantly improve this sector in diverse dimensions, Li et al. [8].

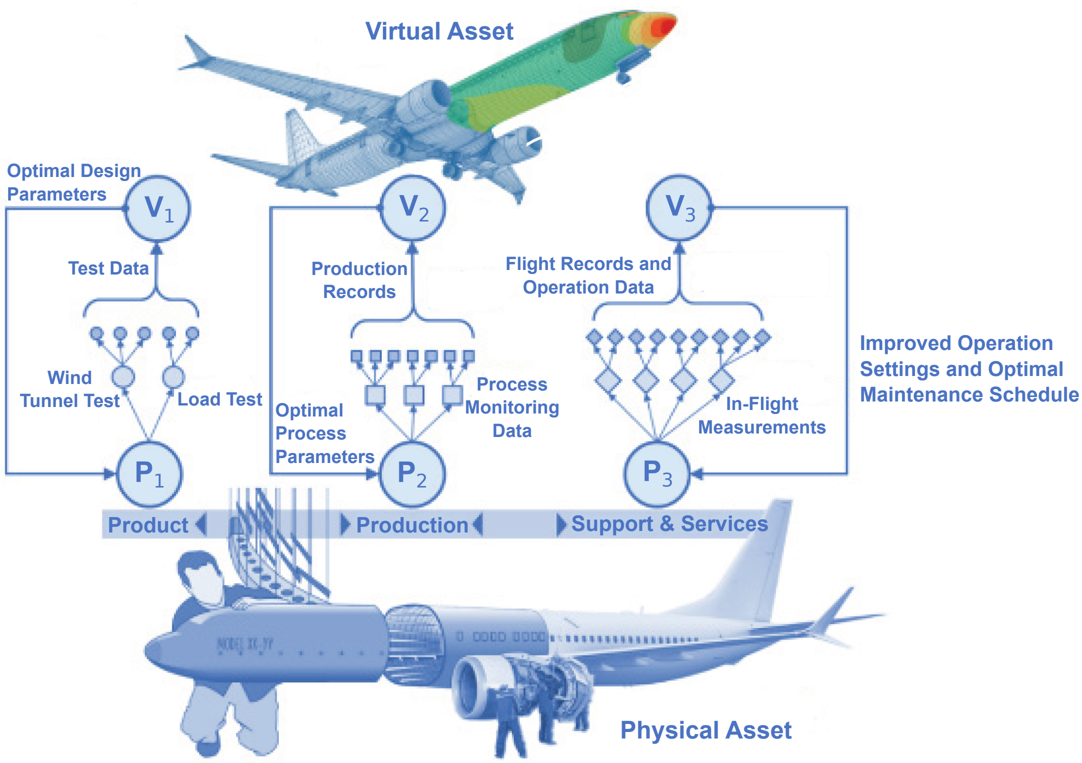

Figure 1. Digital twin concept proposed by AIAA and AIA Digital Engineering Integration Committee. (Adapted from [7]).

In conjunction with these digital advancements, collaborative platforms and cloud-based solutions have become easily accessible, enabling global teams to collaborate seamlessly on aircraft design and development, Chen et al. [9]. Moreover, the application of advanced simulations, such as computational fluid dynamics (CFD) and finite element analysis (FEA), has become more sophisticated, allowing for accurate and comprehensive multi-physical assessments, comprising aerodynamics, structural integrity, and thermal performance. Collectively, these strides in digitalization have ushered in a new era of aircraft design, characterized by enhanced efficiency, sustainability, and innovation across every stage of the aerospace product lifecycle, Benaouali and Kachel [10].

Taking advantage of the diverse artificial intelligence (AI) tools, including machine learning tools, that have been emerging in last decade, opportunities to significantly enhance the capabilities of finite element models through a multitude of avenues are possible. One notable opportunity is the ability of AI tools to greatly improve prediction accuracy, Zhang et al. [11]. By harnessing machine learning algorithms, finite element models can encapsulate complex relationships between input parameters and structural responses, enabling more precise predictions even in scenarios characterized by intricate nonlinearities or uncertainties that traditional analytical methods might struggle to capture. Furthermore, machine learning techniques can be instrumental for surrogate modeling and for calibration and updating of finite element models, Vurtur Badarinath et al. [12]. By assimilating patterns from empirical data, machine learning models can provide informed suggestions for adjusting model parameters. This process translates into refined models that align more closely with real-world behaviors, enhancing the utility of finite element analyses. Machine learning also holds the potential to adeptly address the challenges posed by intricate geometries and varied material properties, due to the complexity and stochasticity of manufacturing and assembly processes.

This manuscript has as main objective the discussion of the potential benefits of integrating digital twins with model updating techniques in the context of aircraft structures life-cycle simulation. This topic has high disruptive potential to improve the design philosophies currently adopted by civil aircraft sector. In addition, it contributes to the growing body of knowledge surrounding aircraft structural simulation and to inspire further exploration and adoption of digital twin technologies in the aerospace engineering domain. Digital twins and model updating techniques constitute innovative tools to address the challenges in simulating and defining the life cycle of aircraft structures and the maintenance intervals. The combination of information from design models with sensors data present high potential impact. This combined approach can significantly improve the design, analysis, and maintenance processes, thereby enhancing the overall safety, performance, and cost-effectiveness of aircraft operations, contributing for a greener aviation, Srivastava [13].

2 Model updating techniques

In current engineering design activities, finite element analysis (FEA) stands as a widely employed computational technique for the structural design and for the anticipation of their responses under diverse loading conditions, Liu et al. [14]. Nevertheless, the instances in which the computed outcomes can fail to exhibit a satisfactory alignment with experimental measurements could restrict the suitability of the adopted model for precise judgements about the structural behavior. In diverse fields, strategies for model calibration have been developed, for instance, for composite fuselage, as proposed by Wang et al. [15] or for wings, as discussed by Sharqi and Cesnik [16].

Model updating techniques can be characterized as a numerical procedures aimed at the incremental refinement of a simulation model, which, for structural purposes, is commonly a finite element model. This refinement occurs through the adjustment of its inherent parameters and underlying assumptions, resulting in a gradual convergence of its behavior, such as static and dynamic structural responses, with that exhibited by the current physical structure under analysis, Friswell and Mottershead [17]. In the realm of structural damage assessment, the methodologies involving the updating of numerical models entails the minimization of residuals across several pertinent structural characteristics. These residuals are computed between the predictions derived from the numerical model and the observed responses exhibited by the real structure. This endeavor can be considered as an optimization problem, wherein the objective function assumes the role of quantifying the dissemblance prevailing between the finite element model and the ascertained measurements. Within this optimization concept, the focal point pertains to the refinement of parameters intrinsic to the numerical model, which concurrently serve as the designated design variables. The multiplicity of optimization strategies amenable to the realization of numerical model updating within this complex framework has been extensively studied for diverse applications, Friswell and Mottershead [17], Marwala [18], Ren and Chen [19], Marwala et al. [20].

According to Alkayem et al. [21], model updating methodologies can be categorized into two main classes: direct methods (typically, non-iterative) and indirect (iterative) methods. The latter category, namely the indirect methods, finds more prevalent utilization due to their capacity to offer a broader spectrum of parameters available for updating. Additionally, indirect methods possess the ability to surmount the limitations encountered by direct methods, Abdullah et al. [22].

From the examples of model updating techniques presented in Figure 2 and proposed by Alkayem et al. [21], computational "intelligence" techniques have been extensively explored in recent years. In this group of techniques, includes the Nelder-Mead simplex method; the sequential quadratic programming technique; fuzzy sets; simulated annealing; evolutionary computation/algorithms; machine learning techniques and the hybrid optimization methods, [18, 23, 24]. In this group, evolutionary algorithms constitute a class of computational techniques inspired by the principles of biological evolution and natural selection. Rooted in the field of optimization, these algorithms replicate the iterative process of selection, reproduction, and mutation observed in the natural world to solve or to optimize complex problems across diverse domains. By representing potential solutions as individuals within a population, and evaluating their fitness based on a defined objective function, evolutionary algorithms iteratively guide the population towards improved solutions over generations. Through the recombination of genetic information and the introduction of random variations, these algorithms explore solution spaces comprehensively, searching for optimal or near-optimal configurations, Vikhar [25].

On the computational "intelligence" techniques, the group of machine learning techniques have been emerging as very promising tools. These techniques offer novel avenues for enhancing the accuracy and efficiency of this process. Machine-learning techniques are typical subdivided into the three main groups: (i) supervised learning;

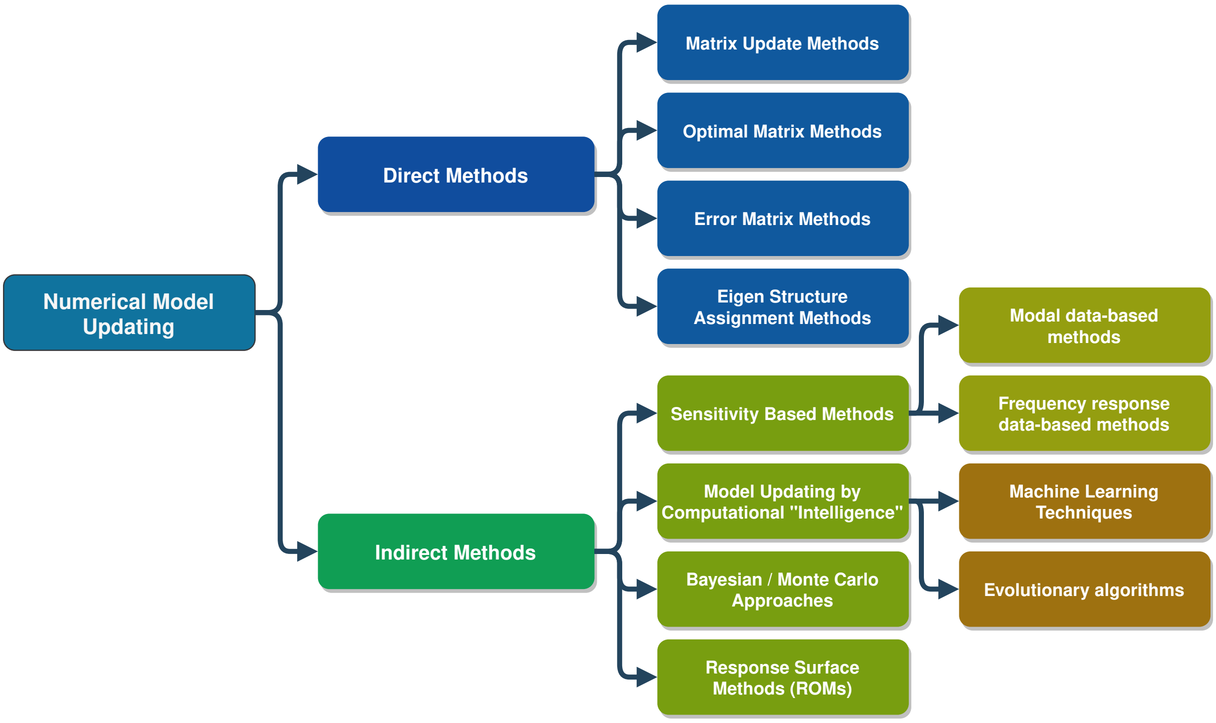

Figure 2. Examples of model updating techniques applicable to finite element models (Adapted from [21]).

(ii) unsupervised learning and (iii) reinforcement learning. The main difference between supervised and unsupervised learning is the model knowing or not what the outputs will be. Reinforced learning is model that learns how to respond to a specific output and by ensuring that each behavior has an effect on the environment, providing reinforcements in the form of incentives and punishments on the model, Sui et al. [26].

Harnessing the power of machine learning algorithms, such as convulsion neural networks (CNNs), graphical neural networks (GNNs), recurrent neural networks (RNNs) and physics-informed neural networks (PINNs), among others, allows to identify intricate complex relationships between the numerical model and measured data. This enables the identification of patterns, correlations, and complex dependencies that might be challenging to discern using traditional methods. These machine learning approaches facilitate the development of data-driven surrogate models, capable of approximating the intricate mapping between input parameters and structural responses. These surrogates can significantly expedite the iterative optimization process inherent in model updating by replacing computationally expensive finite element simulations with rapid predictions from the trained machine learning models, as proposed by Ribeiro et al. [27]. Consequently, the fusion of machine learning techniques with finite element model updating has high potential impact, not only elevating the accuracy of predictions but also introducing an element of computational efficiency that is indispensable for real-world and complex engineering applications.

3 Damage tolerant design

Damage tolerant design is a pivotal design philosophy in aircraft engineering aimed at ensuring the continued structural integrity and safe operation of an aircraft even in the presence of defects, cracks, or unexpected events which instigates structural damages, [28]. This approach acknowledges that despite rigorous maintenance and operational practices, aircraft components may still experience wear, tear, or unforeseen incidents. To address this, damage tolerant design involves the careful consideration of factors such as material properties, structural configuration, and load distribution to minimize the likelihood of catastrophic failure resulting from localized damage. By employing redundancy, load redistribution mechanisms, and fracture-resistant materials, damage tolerant design enhances the ability of aircraft structures to withstand and accommodate various forms of damage, thereby extending the service life of the aircraft while maintaining safety standards. This approach holds particular significance in the civil aviation industry, where safety and reliability are paramount, ensuring that even under challenging circumstances, aircraft can continue to operate safely until scheduled maintenance interventions can be executed.

The integration of digital twin technologies and model updating techniques holds the potential to revolutionize the traditional approach to damage tolerant design in the aerospace industry. Digital twins can provide a dynamic and real-time information about the aircraft structural health, continuously monitoring and analyzing its condition throughout its service. This data feedback enables engineers and decision makers to accurately assess the impact of various forms of damage on the aircraft's structural integrity and performance. By incorporating real-world data into simulations, model updating techniques can refine predictive models to better reflect the actual behavior of the aircraft under different damage scenarios. This iterative process leads to enhanced accuracy in predicting how damage will propagate and affect the aircraft's load distribution, ultimately influencing design decisions and maintenance strategies, Seventekidis et al. [29].

Currently, the real-world data of aircraft structures has been improving through the integration of advanced structural health monitoring (SHM) technologies, Yuan [30]. The SHM systems employ an array of sensors, including strain gauges, accelerometers, thermocouples, among others, to continuously monitor the structural integrity of critical components. The real-time data collected from these sensors offer insights into stress distributions, load variations, and potential defects, enabling operators to promptly detect and assess the extent of damage. This proactive approach to damage detection aligns seamlessly with damage tolerant design philosophy and digital-twins developments, allowing timely interventions and maintenance to mitigate the progression of flaws, reduce maintenance costs, and extend the operational lifespan of civil aircraft.

Figure 3 presents, schematically, the typical curve of the probability of failure, from the structural point of view. The reduction of the probability of failure is linked to the maintenance operations, which restores the residual strength of the structure by repairing all damages detected in the structure. For normal conditions, maintenance operations are pre-programmed with time intervals, Δt based on the design assumptions and fatigue characteristics of the materials. Using digital twins, proactive maintenance planning can be used by detecting and predicting potential structural issues before they escalate, aligning well with the principles of damage tolerant design by allowing timely interventions to mitigate further damage. These time intervals can be adjusted for each aircraft and considering the specific service conditions, (Δt_1, Δt_2, Δt_3, ..., Δt_n), improving the operational time without compromise the structural integrity of the aircraft.

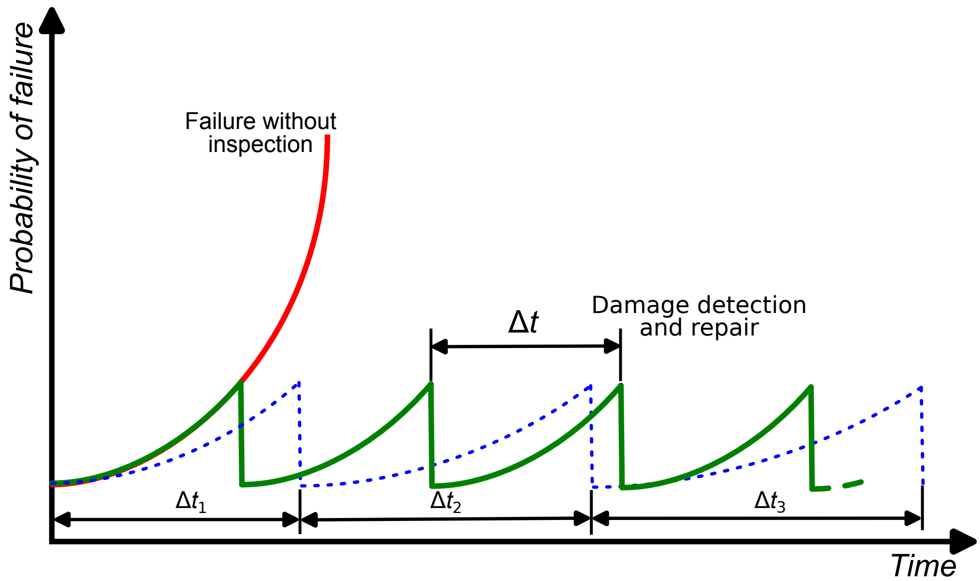

Figure 3. Example of possible impact on the adoption of digital twins and model updating techniques for damage assessment.

With structural health monitoring systems, the integration of data from various sensors and sources requires the development of robust data fusion techniques that can handle different types of data streams, such as strain measurements, temperature readings, and vibration patterns. Once the data is pre-processed and integrated, advanced analytic techniques, including machine learning and artificial intelligence algorithms, can be applied to extract meaningful insights, identify patterns, and detect anomalies based on the numerical models and the respective updates. These insights can be used to update and refine digital twin models, making them more representative of real-world conditions and enabling more accurate predictive simulations. Ultimately, by effectively managing the abundance of data from SHM systems, the accuracy and reliability of structural numerical models and digital twins can be substantially improved, leading to safer and more efficient aircraft operations, Broer et al. [31]. The combination of digital twins and model updating techniques can enable a more efficient utilization of resources in the damage tolerant design process, Wild et al. [32]. Traditional methods often involve conservative assumptions to account for uncertainties in structural behavior under damage conditions, leading to over-engineered components and increased weight. By leveraging real-time data and accurate simulations, digital twins provide a deeper understanding of actual loading condition and stress distributions within damaged structures. This information can guide the refinement of finite element models and allow for more accurate predictions of residual strength and fatigue life. Consequently, aircraft manufacturers can optimize component designs and maintenance operations to restore the aircraft residual strength, achieving a balance between safety and weight savings. This optimized approach aligns with the tenets of damage tolerant design, aiming to maximize the structural lifespan while minimizing unnecessary material, fuel consumption and maintenance costs.

4 Conclusions

The integration of digital twin technology and model updating techniques is enabling a transformative era in aircraft design and the broader aerospace industry. These advancements have potential to enable a profound shift from traditional design paradigms to dynamical updated, data-driven processes. The current capability to continuously monitor the aircraft and seamlessly update simulation models ensures that aircraft structures are built to withstand real-world conditions, leading to improved safety, reliability, and sustainability.

Considering the damage tolerant design, these technologies offer a new level of insights into the structural health of aircraft, allowing engineers to accurately assess the effects of damage and develop more accurate predictive models, individualized for each aircraft. By leveraging data to inform maintenance and repair decisions and optimize designs, digital twins and model updating contribute to longer-lasting, safer, and more cost-effective aircraft structures.

Taking into account the fast evolution of diverse machine learning tools applied to diverse engineering simulation problems, disruptive approaches can be developed supporting these digital twins. These machine learning tools can handle complex and large-scale data, which can be obtained from structural instrumentation and integrating this data to update numerical models. These approaches not only accelerate design iterations but also optimize the accuracy of simulations, resulting in more reliable insights into aircraft performance, structural integrity, and maintenance needs.

In essence, the integration of digital twins and model updating techniques based on machine learning offers a paradigm shift in the damage tolerant design philosophy, enabling more informed, adaptive, and resource-efficient strategies for ensuring the structural integrity and safety of aircraft throughout their operational life.

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