A primer to digital twins in the aeronautical and aerospace industry

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ABSTRACT: *The Digital Twin (DT) technology has evolved significantly since its inception during NASA's Apollo program in the 1960s, becoming essential in the aerospace industry and beyond. This paper explores the historical development of DTs, transitioning from early "Physical Twins" to sophisticated virtual models driven by advancements in the Internet of Things (IoT), machine learning, and data analytics. In aerospace, DTs improve product lifecycle management, operational efficiency, and cost-effectiveness by enabling real-time monitoring, predictive maintenance, and high-fidelity simulations of aircraft and spacecraft systems. The study outlines the core components of DTs physical reality, virtual representation, and their interconnectedness and presents real-world applications such as optimizing heavy fuel aircraft engines and tidal turbines. Despite advancements, challenges like data integration, sensor reliability, and real-time processing remain. Nonetheless, the continuous development of DT technologies promises enhanced performance, safety, and innovation across multiple industries. The paper concludes by emphasizing the transformative role of Digital Twins in the future of technology and industrial practices.*

KEYWORDS *- Digital Twin, Aerospace, Real-time Monitoring, Optimization*

I. INTRODUCTION

The concept of the Digital Twin (DT) has evolved significantly since its inception, with aerospace being one of the pioneering industries to adopt this technology. Originally conceived during NASA's Apollo program in the 1960s, the DT has matured into a critical tool for real-time monitoring, optimization, and decision-making. The formalization of the DT concept came in 2002 through Grieves' work [1], which laid the foundation for its application in various sectors.

In aerospace, Digital Twin technology plays a pivotal role in improving product lifecycle management, enhancing operational efficiency, and reducing costs. By creating accurate virtual replicas of physical systems, such as aircraft and spacecraft, DTs enable continuous monitoring and simulation, which allows engineers to predict performance, identify issues before they occur, and optimize maintenance schedules [2], [3]. This paper provides an overview of the state of the art of Digital Twin technology in aerospace, focusing on its evolution, core components, and cutting-edge applications that are driving innovation in the industry.

II. HISTORICAL CONTEXT

The concept of the Digital Twin (DT) has evolved significantly, starting with NASA's Apollo project in the 1960s. From early "Physical Twins" to advanced digital frameworks, DTs have transformed into essential tools for monitoring, optimization, and innovation across industries.

2.1 Beginnings (1960 – 2000)

During NASA's Apollo project in the late 1960s, the concept of a 'Twin' began to take shape in the aerospace industry. The idea involved having two capsules: one destined for launch and another remaining on Earth. Both would contain identical components, and any alteration made to the launch-bound capsule would be mirrored in the one on the ground. This approach allowed engineers to test solutions on the Earth-bound capsule if issues arose during the mission before instructing the astronauts.

Known as the "Physical Twin," this concept is often dismissed due to its exorbitant costs and the added difficulty of replicating the real object's conditions in a laboratory setting. Frequently, this proves impossible, rendering the conclusions drawn from the Physical Twin non-extrapolable.

2.2 Formalization (2000 – 2010)

The concept was first formalized by Grieves in a 2002 conference on Product Lifecycle Management (PLM) [4], where he presented a slide titled Conceptual Ideal for PLM. This model comprised a real space, a virtual space, and the data link connecting them.

At that time, the enabling technologies for Digital Twins were insufficiently developed, as noted in [5]. Consequently, while the concept evolved, technological limitations such as hardware virtualization, the Internet of Things (IoT), machine learning, and computational capacity made implementation exceedingly difficult.

In 2005, Grieves referred to this concept as "Mirrored Spaces" in his paper [6]. It wasn't until 2006 that he began using the term "Digital Twin" in [7], although he also referred to it as a "virtual doppelganger."

2.3 Consolidation (2010 – 2014)

By 2010, the concept gained significant traction, especially in the aerospace industry, appearing as a key technology in NASA's roadmap. John Vickers decisively coined the term "Digital Twin" during this period. Both NASA and the U.S. Air Force adopted the concept, marking a transition from conceptualization to formalization. In [8] (2012), the Digital Twin is heralded as the future of vehicle development and construction. The authors argue that integrating high-fidelity simulations, real-time vehicle status, maintenance history, and comprehensive data from the entire fleet can achieve unprecedented levels of safety and reliability.

Numerous companies, including Airbus and Boeing, initiated programs to develop their own Digital Twins. The concept was gaining popularity through Industry 4.0, aiming to enhance quality and optimize manufacturing processes.

2.4 Expansion (2015 – Present)

In this phase, the development of Digital Twins has expanded considerably, with a burgeoning body of literature on the subject [2], [3]. Advances in enabling technologies have made the concept more accessible, prompting many smaller companies to invest in its development. Siemens and General Electric have developed Digital Twin platforms for real-time monitoring, inspection, and maintenance [9].

The feasibility of Digital Twins began to be scrutinized. In 2017, the U.S. Air Force estimated that developing a Digital Twin for the Next Generation Air Dominance (NGAD) aircraft would cost between $1 and $2 trillion and require over a century to complete (an effort comparable to the Manhattan Project).

This period also saw publications that further expanded and refined the concept. For instance, Tao and Zhang proposed a four-dimensional Digital Twin framework comprising a physical entity, virtual model, service, and Digital Twin data [10]. In [5], it was suggested that the data flow between each module should be considered a crucial feature of the model. Consequently, it was assigned its own dimension, leading to the consolidation of the five-dimensional Digital Twin model framework [3].

Definitions of Digital Twins vary depending on the application domain, use cases, and authors. Kritzinger proposed classifying Digital Twins into three types based on their level of integration with the physical counterpart, specifically, whether the data flow between them is automatic: Digital Model, Digital Shadow, and Digital Twin [11]. This approach was critiqued by Grieves, who disagreed with the classification, particularly the concept of a "Digital Shadow" [12]. However, it was expanded upon by other scholars like Alexander Barbie, who in 2022 proposed the ARCHES Digital Twin framework [13]. Barbie offered formal definitions of related concepts often confused with Digital Twins such as Digital Shadow, Digital Twin Prototype, and Digital Model and provided a formal specification using Object-Z notation [14]-[16].

Grieves suggested a model featuring three types of Digital Twins corresponding to different stages of a product's life cycle: the Digital Twin Prototype, Digital Twin Instance, and Digital Twin Aggregate [17].

On the industrial front, IoT platforms have been evolving into platforms that aim to facilitate Digital Twin implementation. Lehner identified a set of requirements these platforms should meet; however, none fully satisfy all the criteria, indicating that substantial work remains to be done [18].

In the aerospace industry, the term aero-DT is defined through three key dimensions: the physical side, which includes sensors and functional infrastructure; the virtual side, consisting of analytical models and artificial intelligence (AI); and the connection, referring to data transmission and the human-machine interface [19].

Digital Twins (DTs) in this sector optimize the product lifecycle, improve efficiency in new product development (NPD) and smart manufacturing, facilitate predictive maintenance and operations (O&M) management, reduce costs and operational risks, and enable high-fidelity simulations for informed decision-making throughout the entire product lifecycle [19].

III. KEY COMPONENTS OF DT

The various definitions of Digital Twin (DT) make the conceptualization of its components somewhat diffuse and, above all, dependent on the application domain. However, we can identify three common components across the definitions discussed earlier [20]:

3.1 Physical Reality

This is the origin of our data flow. It represents the "real" product, including sensors, actuators, embedded software, and physical connections used [16]. Everything that will be modeled and considered in the creation of the Digital Twin falls under this component. It is the source of data, which, through the connection layer, will be utilized by the virtual side for processing and analysis.

3.1.1 Physical System

The physical system refers to the set of tangible components and devices that make up the product or infrastructure to be replicated [16]. This includes machines, equipment, and hardware that enable the operational function of the system. In most cases, the object will be a manufactured product, such as the "main bearing" of an aircraft [21], but there are also cases where the physical system could be a living organism or an aspect of a natural environment, as seen in the health or agriculture domains [14].

3.1.2 Physical Environment

These are the environmental factors that affect the physical system. In the DT of an airplane, for instance, we might consider factors like external temperature, light, wind, or turbulence, as these affect the airplane itself [22]. The importance of this component varies across different applications. In wind farms, wind conditions will be a critical factor [23]. Incorporating models that predict or offer stochastic scenarios of future environmental states enhances the success of DT implementation [24].

3.1.3 Physical Process

This refers to the set of processes by which the physical system interacts with its environment. These processes originate in the physical environment and manifest in the physical system, causing a state change. The physical system and environment have a bidirectional interdependence. An elevation on the temperature in an engine could reduce its lifespan, while the temperature increase may have been caused by actions carried out by the physical system itself. These processes are also subject to simulation by the DT. In [25], the growth of cracks in alloy 7075-T7351 of airplane wings is simulated [26].

3.1.4 Sensors

Sensors are vital for the Digital Twin. They are the "senses" of our Digital Twin. The three components mentioned above are observed by the "virtual representation" through sensors, which collect the data to update the state of the virtual counterpart. New materials are being developed which can act as sensors in crack detection. This way they can be used to check the crack status of the main frame or other relevant structures [27].

3.2 Virtual Representation

This component encompasses all the software pieces used in the Digital Twin.

3.2.1 Virtual System

The virtual system is the detailed and functional digital representation of the physical system, created using models as discussed in section 3.2.4. This component allows us to experiment and analyze the behavior of the physical system.

3.2.2 Virtual Environment

The virtual environment digitally simulates the external conditions affecting the physical system, incorporating variables such as climate, topography, and other environmental factors. It provides data as input for process models that will update the state of the virtual system. This process may also operate in reverse.

3.2.3 Virtual Processes

Virtual processes demonstrate how the virtual system undergoes state changes through computational models of the corresponding physical processes. These models simulate the transformations experienced by the physical system. By replicating the relationships between inputs and outputs that affect the system's state, we can predict future states and evaluate different scenarios. This field of simulation is growing rapidly, thanks to advances in AI, machine learning, and other simulation techniques [21], [28], not only in terms of physical models but also process modeling [29].

3.2.4 Modeling

There are various types of models used in Digital Twin systems:

Physics-based models, also known as "model-driven" models, are defined using mathematical models and physical formulas. They are advantageous because they are strictly defined with mathematical formulas, making them more understandable in terms of model explainability [30]. That is, the functioning of the models is clear, and if they fail, it is possible to identify the error in the model's design [31]. These models are also easily transferable between domains when the problem is similar, with minor adjustments.

Data-driven models are those that derive their logic from collected data. With improvements in IoT and sensors, the amount and quality of data available for collection has increased. Furthermore, computational capacity and the availability of machine learning tools have made it cheaper to develop high-performing data-driven models. These models help tackle situations where we lack theoretical understanding of the system's workings, as they aim to explain system behavior based on changes in variables [32].

3.3 Connection

This component links the physical and virtual spaces. The connection must be bidirectional, which differentiates Digital Twins from concepts like the "digital shadow." The exchange of information can be automatic or manual, though this remains a debated issue in the scientific literature [17], [12], [16].

3.3.1 Physical to Virtual Connection

The objective of this process is to update the virtual counterpart with the current state of the physical component. It is essential to maintain coherence between the physical and virtual systems, ensuring the Digital Twin accurately reflects the real-world conditions.

Data is first collected from the sensors installed on the system and its environment. These sensors provide information on variables like temperature, pressure, and vibrations. Manual inputs, such as repair histories and visual inspections, are also incorporated to offer a more comprehensive view of the system's status. Techniques to improve data quality can be applied. In [33], a model that fuses noisy wind-tunnel and biased simulation data using a Bayesian framework is proposed, showing improved robustness with limited data and similar results to proper orthogonal decomposition with enough data.

Next, the collected data is interpreted and analyzed. This involves preprocessing to eliminate noise and anomalies, as well as data curation to correct errors and standardize formats, ensuring the quality and consistency of the information.

Finally, the processed data is used to update the virtual representation. The states may directly match the sensor readings, but in some cases, the state will be inferred from the measurements. Techniques like data fusion can be crucial in this step.

In the domain of intelligent maintenance, for example, the degradation state of a component might be updated based on all available data, including sensor readings.

3.3.2 Virtual to Physical Connection

For a Digital Twin to be truly "digital," there must be an exchange of information between the digital and physical twins. In most cases, this information exchange is intended to be automatic. For instance, if the Digital Twin identifies that increasing the fuel injection of an engine by a certain percentage extends its lifespan, this action would be automatically implemented, i.e., the physical twin would have actuators [16]. However, in some cases, either due to technical limitations or ethical concerns, this automatic exchange may not be feasible, such as in the case of DTs in humans[34]

IV. REAL CASE SCENARIOS

In the study [35], a digital twin system is created for 2-stroke heavy fuel aircraft engines (2S-HFAE) to optimize manufacturing processes. Through simulation via DT, they achieve over a 4% improvement in gas exchange performance under various engine speed and load conditions. The article proposes a DTAF (Digital Twin-Assisted Framework) designed to optimize the gas exchange system in terms of performance and manufacturing, consisting of five key components (5-dimensional DT) [36], [3]:

The Physical Entities represent the real-world components, such as the engine and the gas exchange system, which are equipped with sensors for continuous real-time monitoring of operational conditions. The Virtual Modules simulate the physical processes, enabling optimization and decision-making within a virtual environment. These modules encompass various types of digital twins, including Behavior, Environment, Performance, Structure, Material, and Craft Digital Twins.

The DT Service System is responsible for managing the data from both the physical entities and the virtual modules. It plays a crucial role in supporting the optimization of performance, design, and manufacturing through data fusion and analysis. The DT Data consists of real-time data generated from the physical entities and the virtual modules, driving continuous updates and iterative optimization of the system. Connections between all components facilitate data feedback and communication, ensuring enhanced interaction and operational efficiency throughout the system.

Together, these components work cohesively to improve both optimization and manufacturing processes, reducing the need for extensive physical testing while supporting ongoing performance enhancements.

The article also outlines a six-step optimization method based on digital twins. The first step involves the setup of Behavior and Environment DTs, where a virtual engine model is created using real-time experimental data to refine the simulation of key parameters, such as cylinder pressure and exhaust gas concentration. The second step, Performance DT and Optimization via Design of Experiments (DoE), uses DoE techniques to optimize system parameters, verifying their effectiveness through simulations and real-world data.

In the third step, Material, Manufacturing, and Structure DTs are used to adjust virtual designs, refining assembly relationships based on material properties and manufacturing processes. During the Real Manufacturing Process and Feedback phase, errors and dimensional data from the actual manufacturing process are fed back into the system, allowing for adjustments to the simulations to better align with the physical reality. The Real Performance Testing and Validation step then validates the accuracy of the simulations through real-world tests, helping to reduce the need for further physical testing. Finally, the Final Product and Continuous Analysis phase involves the production of the optimized engine, while ongoing data analysis allows for real-time optimization adjustments throughout the engine’s lifecycle.

For Virtual Engine Modeling, GT-Power is employed to simulate the engine, including the intake, supercharging, crankshaft, cylinder, and exhaust systems. The model's accuracy is continually improved by incorporating experimental data, reducing errors in parameters such as brake torque and intake flow by up to 88%.

Lastly, Iterative Optimization with DoE is used to study the impact of variables like valve timings on engine performance. Genetic algorithms are applied to optimize valve timing, enhancing system parameters without the need for physical testing.

The article demonstrates how the Digital Twin-Assisted Framework (DTAF) optimizes engine performance and manufacturing. By adjusting manufacturing parameters via the Virtual Craft DT, they improved tolerance adherence between virtual and real models, achieving a 4% improvement in performance and efficiency, mainly through valve timing optimizations.

Apart from this example, there are more work that demonstrates the viability of using Digital Twin.

As shown in [26], Digital Twin (DT) technology can be used for real-time monitoring and performance evaluation of horizontal axis tidal turbines (HATT), leveraging CFD simulations, Kriging interpolation, and machine learning to optimize hydrodynamic assessments and flow field monitoring.

In the article [37] intelligent maintenance of an Aircraft Main Bearing is studied by implementing a DT. With sensors for the temperature, vibration and lubrication, the Remaining useful life (RUL) is predicted. This way the maintenance is applied based on the RUL instead of predefined timings.

V. Conclusion

The concept of the Digital Twin (DT) has evolved from its origins in aerospace applications, particularly NASA's Apollo program, to become a transformative tool in industries ranging from manufacturing to healthcare. As technological advancements continue to address the challenges of real-time data processing, machine learning, and system simulation, the potential of Digital Twins to optimize performance, reduce costs, and improve safety is increasingly evident.

The historical progression of the Digital Twin, from its conceptualization in the 1960s to its formalization in the early 2000s and eventual widespread adoption in the 2010s, reflects the growing sophistication of the enabling technologies and the expanding range of applications. The development of Digital Twins has been driven by the convergence of several technologies: the Internet of Things (IoT), sensor networks, data analytics, and machine learning, all of which contribute to the creation of high-fidelity, real-time virtual models that mirror the physical world.

Despite significant progress, challenges remain in fully realizing the potential of Digital Twins. The complexity of data integration, the need for accurate and reliable sensor networks, and the necessity of real-time data processing are hurdles that still require attention. However, as demonstrated by the aerospace, automotive, and manufacturing sectors, the benefits of Digital Twins in improving product lifecycle management, predictive maintenance, and process optimization far outweigh these challenges. The development of frameworks such as the Digital Twin-Assisted Framework (DTAF) highlights the immense value that these models can provide, from reducing reliance on physical prototypes to optimizing system performance iteratively.

Real-world case studies, such as those implemented in heavy fuel aircraft engines and tidal turbines, underscore the practicality of Digital Twin systems in optimizing operational efficiency and manufacturing processes. Through simulations, data fusion, and iterative optimization, Digital Twins facilitate improvements in performance and design, while also enabling ongoing adjustments throughout the lifecycle of complex systems.

In conclusion, the Digital Twin marks a major advancement in modeling, analyzing, and optimizing physical systems through virtual counterparts. As adoption grows and enabling technologies evolve, its applications will expand, driving innovation and efficiency across industries. Future developments will focus on enhancing interoperability, improving simulation accuracy, and addressing ethical concerns around autonomous decision-making. Ultimately, Digital Twins will remain pivotal in shaping the future of technology and industry.

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