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Smart Aircraft Monitoring Using AI-Driven Digital Twins and IoT-Based Data Acquisition

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Abstract

The convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and Digital Twin (DT) technologies is reshaping modern aerospace systems by enabling intelligent, predictive, and data-driven maintenance operations. This paper presents a modular and scalable Digital Twin framework that integrates IoT-enabled real-time data acquisition with AI-driven analytics to support aircraft lifecycle management. The proposed approach combines data-driven models—such as Random Forests and deep learning—with physics-based simulations to enhance system diagnostics, anomaly detection, and remaining useful life (RUL) estimation. A layered architecture is outlined, incorporating edge computing, cloud services, and API connectivity to facilitate seamless communication between physical systems and their virtual counterparts. The paper also addresses current challenges in interoperability, model fidelity, and regulatory constraints, while offering a roadmap for implementing hybrid AI-IoT Digital Twins in real-world aerospace applications. This work aims to guide the design of next-generation aviation systems that are adaptive, autonomous, and resilient across operational contexts.

Keywords: Digital Twin, Artificial Intelligence, Internet of Things, Predictive Maintenance, Aerospace, Cloud Computing, Edge Analytics, Lifecycle Management, Hybrid Modelling, Aircraft Systems.

Introduction

In the past twenty years, the introduction of the Internet of Things (IOT), has changed the way data is exchanged between different sources. The introduction of Digital Twin which is basically integration of Big Data Analytics and AI model. Industry 4.0 represents the fourth industrial revolution characterized by the fusion of digital, physical, and biological systems. Among the key enablers of this revolution is the Digital Twin, a concept that integrates real-time data from physical systems with their virtual counterparts. According to the Encyclopedia of Production Engineering, a Digital Twin is a virtual representation of a unique, active "product," which may be a physical device, object, machine, service, an intangible asset or a system that includes a product and its associated services can be represented by developing a synchronized virtual model of assets or processes. This allows organizations to assess performance, anticipate potential failures, and enhance operational efficiency.

Digital Twin models are gaining more and more interest for their potential and strong impact in application fields, such as manufacturing, aerospace, healthcare, and medicine. Today, technology is used across many industries to provide accurate virtual representations of objects and simulations of operational processes. According to a 2019 Gartner survey, Digital Twin technology had begun to gain widespread adoption among organizations. According to Global Market Insights, the Digital Twin market, valued at

$8 billion in 2022, is projected to grow at a CAGR of approximately 25% from 2023 to 2032.Digital Twin is an advanced technology transforming industries by replicating products, processes, or services in a virtual environment. t enables the creation of digital counterparts of physical assets, offering real-time feedback to engineers. This virtual mirroring allows for faster identification and resolution of physical issues. It also supports the design and development of more efficient, higher-quality products. Ultimately, Digital Twin technology accelerates value realisation & enhances operational performance. Components on the physical side are mainly to support data collection and computing. Sensors are the 'must have'components in every form of DT. Coupled with data transmission technologies, they guarantee that DTs can realise real-time data collection and synchronisation. Various sensors enrich the types of data that can be collected, from text, audio, hyper-spectral images, video, temperature, pressure etc. to behaviour and biological characteristics

A notable early application of Digital Twin technology occurred in 1970, when NASA engineers used a simulator essentially a twin of the Apollo 13 command module and a separate twin of its electrical system to troubleshoot critical issues. They successfully completed the process in under two hours, ultimately saving the lives of the three astronauts aboard the spacecraft. NASA engineers successfully completed the procedure in less than

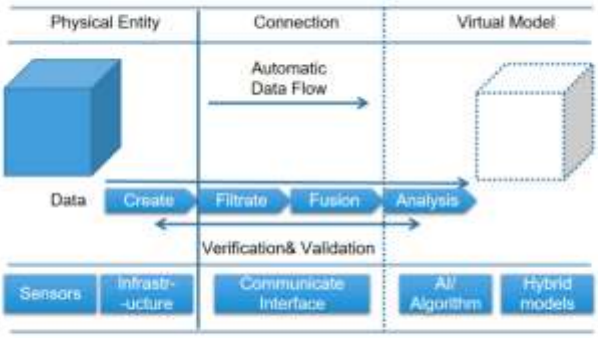

Fig. 1 components of DTs

two hours, ultimately saving the lives of the three astronauts aboard.[7] This remarkable early use of the technology set the stage for its future development, and it has advanced significantly since then. NASA currently utilizes Digital Twin technology in the development of advanced vehicles and aircraft for future missions.

The Digital Twin opens According to Global Market Insights, the Digital Twin market, valued at $8 billion in 2022, is projected to grow at an approximate Compound Annual Growth Rate (CAGR) of 25% from 2023 to 2032. Digital Twin technology has transformed industries by digitally replicating nearly every aspect of a product, process, or service. It enables the creation of digital replicas of physical entities, allowing engineers to receive insightful feedback from the virtual environment. This innovation allows companies to quickly identify and address physical issues, design and improve products, and achieve value and benefits at a faster pace than before. Additionally, Digital Twin technology helps businesses optimize their processes and overall performance. The traditional approach of developing a product and improving it through successive versions and release, is no longer sufficient. By utilizing a virtual design approach, the optimal efficiency of a product, process, or system can be identified and achieved by analyzing its characteristics and performance capabilities. A virtually based design approach allows for the identification and development of the highest possible efficiency for a product, process, or system by analyzing its characteristics, performance capabilities, and potential issues.that may emerge. Digital Twin acted as a virtual platform for examining functional interactions and their effects on electricity production. This approach offered a cost-effective and efficient alternative for analyzing control process behaviors while minimizing downtime. Additionally, it contributed to improved plant reliability and better resource management. By utilizing a Digital Twin of plant systems and processes, employees can gain valuable insights into operations within a virtual setting. Enhanced plant reliability and improved resource utilization were also highlighted as key benefits. Additionally, employees can gain insights into plant operations by interacting with the Digital Twin of systems and processes in a virtual environment.

2. LITERATURE SURVEY

Technology has significantly transformed both the education sector and various industries.However, education has not adopted the technological advances at the accelerated pace of industry. As a consequence, in education, there is a vast array of technologies available that are not yet explored but they could help update teaching and learning methodologies. In knowledge-based economies, in which having a specialized labor force is critical, technology plays a pivotal role in supporting the development of skilled personnel. In the future, the technologies reviewed in this research will open new forms of learning that we cannot even imagine. However, more research is needed to determine their pedagogical effectiveness for the different types of students (styles of learning); in addition, these technological tools should not be seen as substitutes for traditional teaching methods but as complements to improve the learning processes and take education to a higher level. The advantages of the considered technologies are numerous. Each approach has its unique advantages, yet they all share a common feature: they provide an engaging educational experience that actively involves students. not even perceive they are learning. They offer flexibility, letting students acquire knowledge and practice their skills or competencies when they consider it is more convenient. These technologies help cultivate a range of essential competencies, including empathy, spatial awareness, creative and analytical thinking, innovation, and effective problem-solving skills that are increasingly vital for the future workforce. However, access to these tools remains limited due to their high implementation costs and the need for specialized infrastructure and network capabilities, which can pose significant challenges, particularly in developing nations. Additionally, health concerns such as visual strain and ergonomic shortcomings must be addressed to ensure their safe and effective use. Finally, there is a need for technology regulation regarding privacy and ethical issues.[1]

Cutting-edge technologies like the Internet of Things (IoT), cloud computing (CC), big data analytics (BDA), and artificial intelligence (AI) have significantly accelerated the evolution of smart manufacturing. A critical foundation for smart manufacturing is the integration between digital and physical domains, which more and more manufacturers are adopting. Cyber–physical systems (CPS) and digital twins (DTs) are emerging as key enablers of this integration and have attracted widespread interest from both researchers and industry professionals. By incorporating feedback loops where physical and digital systems influence each other, CPS and DTs enhance manufacturing with improved efficiency, adaptability, and intelligence. While both rely on close cyber–physical connectivity, real-time responsiveness, organizational alignment, and collaborative operation, they differ in several respects—such as their origins, development paths, implementation strategies, cyber–physical mappings, and foundational components. This paper explores these distinctions and connections in depth. Currently, there is no universally accepted definition for "new IT," though it can be seen as the convergence of industrial, information, and intelligent technologies. It represents both an upward evolution of traditional IT and a

cross-disciplinary integration with various sectors. The IoT, CC, BDA, and AI are the core elements of new IT. In the manufacturing sector, digitalisation has led to the generation of vast and diverse data sets by industrial technology-driven resources (see Fig. 1). The Internet of Things (IoT) enables real-time data collection, which can then be stored and processed. Cloud computing (CC) facilitates efficient handling of this data by dynamically allocating computing and storage resources as needed. Meanwhile, big data analytics uncovers valuable insights and hidden patterns within the data, enhancing decision-making and enabling more intelligent responses to evolving service demands. Thus, the IoT,CC, BDA, and AI play important roles in new IT.[2]
information technology, and intelligent technology Alongside ongoing advancements in artificial intelligence, the past decade has witnessed widespread adoption of broadband and pervasive connectivity, the deployment of embedded sensors capturing rich, high-dimensional data, and significant progress in big data technologies data processing techniques and cloud computing. The combined application of these technologies has given rise to digital twins—intelligent virtual representations of physical systems. Today, Digital Twin (DT) technology is being actively developed and adopted to enhance efficiency

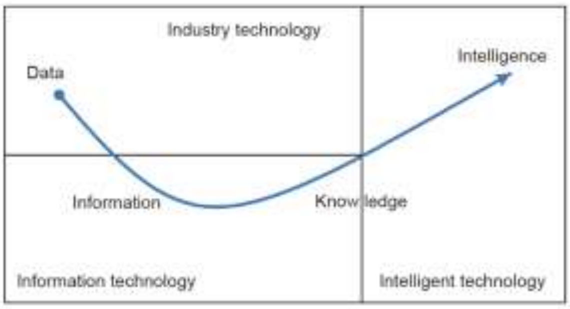

Fig.2 Integration of industrial technology

in various manufacturing and aviation processes. In contrast, its use in healthcare and medicine remains in the early stages of exploration and implementation.its early development stage. This paper presents findings from a study that examines the current definitions of Digital Twin (DT) technology, identifies the key attributes a DT should possess, and explores the various domains where DT applications are actively emerging. In the manufacturing sector, numerous studies leverage DTs to enhance every phase of the product development and production lifecycle. For example, Rosen et al. emphasize that DTs can facilitate the creation of a computerized system capable of overseeing each stage of manufacturing through a modular framework. Specifically, they propose a Smart Manufacturing model composed of autonomous modules that perform complex tasks independently, make decisions from multiple options, and adapt to failures or unexpected conditions without disrupting the operation of other modules—thereby eliminating the need for supervisory-level adjustments. Achieving this level of autonomy requires modules to access highly accurate, real-time information about both the product and the ongoing process, which can be realised through the use of high-fidelity digital twins virtual replica of the physical entities, i.e. a DT. In the illustrated context, Digital Twins (DTs) enable ongoing interaction between the digital system and its corresponding physical asset. While Rosen's work underscores the potential of DTs in manufacturing, it tends to portray them primarily as detailed models or simulations capable of real-time communication with their physical counterparts—an interpretation that may oversimplify the concept. DTs should not be mistaken for conventional simulations or the avatars found in virtual or augmented reality applications.

Although DTs are often conceptualised as three-dimensional representations where virtual models and physical components exchange information via established connections, some researchers—particularly in the context of DT-based smart shop floors—place greater emphasis on the intelligent features (termed "services") integrated into the digital elements, as well as on the aggregation and interpretation of data from multiple sources. In addition to the physical space (PS), its digital counterpart or virtual space (VS), and the communication links connecting them, the authors introduced two more critical components: the Service System (SS), which hosts intelligent functionalities, and the Digital Twin Data (DTD), representing the consolidated data stream supporting DT operations which are processed by SS. The Service System (SS) functions as a unified software platform designed for the management, control, and optimization of operations. It encompasses a range of sub-services that deliver targeted solutions in response to specific demands originating from both the physical space (PS) and virtual space (VS). Meanwhile, the Digital Twin Data (DTD) serves as a centralized repository, housing both real-time and historical data. This includes integrated information from the PS, VS, and external sources. By consolidating diverse data streams from a heterogeneous environment, the DTD plays a vital role in ensuring the availability of accurate, consistent, and comprehensive information to support decision-making and system intelligence. While DT technology in manufacturing is appreciated both for The contribution of this paper also consists in the illustration of the two possible lifecycles for DTs. The first lifecycle describes the life of a DT that starts living in the design phase of its physical twin, which is not existent yet; when the physical twin is built, the DT and its twin live together in seamless communication and interaction. The second scenario regards a DT that is created when the physical twin has already being operating for a while (e.g. in the case of a manufacturing device that becomes a connected device through Industry 4.0 solutions); in this case the DT must be connected to the physical twin, and the two continue their life in seamless interaction.Allowing predictive maintenance and for its capability of optimizing and speeding production in the aviation field the DT is mainly used as a mean for predictive maintenance [3] Smart manufacturing has emerged as a key strategic priority across leading global manufacturing initiatives, including those spearheaded by major industrialized nations like Industry 4.0 and Industrial Internet. Sensors and data transmission technologies are being progressively integrated across various phases of a product's lifecycle ranging from design and manufacturing to distribution, maintenance, and eventual recycling to enable continuous data collection.Big data analytics can make full use of the data to discover failure causes, streamline a supply chain, optimize product performance, and enhance the production efficiency. A major challenge in smart manufacturing is establishing a seamless connection between the physical and virtual environments. The rapid development of simulation, data acquisition, data communication, and other advanced technologies have triggered greater interactions, than ever before, between the physical and virtual spaces. The significance of the Digital Twin (DT), defined by its integration of cyber and physical systems, is gaining growing attention from both academic researchers and industry professionals. DTs and big data analytics are mutually reinforcing technologies on account of smart manufacturing. Digital Twins (DTs) enable the seamless integration of physical and virtual data across the entire product lifecycle, resulting in the generation of large volumes of data suitable for advanced analytics. The insights derived from this analysis can then be applied to enhance the performance of products and processes in the physical domain. Moreover, DTs provide cyber-physical manufacturing systems with real-time information about actual conditions and operational status in the physical world.Such information can enhance a manufacturing system’s intelligence regarding analytical assessment, predictive diagnosis, and performance optimization. DTs can visualize and update the real-time status,which is useful for monitoring a production process. Weyer predicted that DTs represent the next generation of simulation.Hence, DTs play a critical role in developing advanced cyber physical production systems. They suggested that because Digital Twins can synchronize physical and virtual environments, human operators can rely on them to oversee complex production processes, make real-time adjustments, and drive optimization efforts.DTs can facilitate the adjustment of production operations based on both practical situation and simulation. Rosen et al.discussed the application of DTs in production operations. Because Digital Twins are capable of integrating diverse data types—such as environmental, operational, and process-related information—autonomous systems can adapt to changing conditions even during active operations. For instance employed a combination of shape memory alloys, sensory particles, and finite element analysis to detect, monitor, and assess structural damage in commercial aircraft wings. [4].

DT-IIOT leverages digital twins to create digital systems that integrate control, communication, and computing (3C) of the cyber-physical integrated Internet of industry The control subsystems in IIoT systems represent industrial control systems such as supervisory control and data acquisition (SCADA), etc.. The communication subsystem transmits sensing data and actuating commands between sensors, controllers, and actuators. The computational subsystem provides computational resources and computes the actuation signals. AI paradigms, such as neural networks, deep learning, and reinforcement learning are valuable data-driven techniques that solve prediction, classification, and automation problems. Digital twin interconnects the real-world domain through data exchanges, where the data becomes naturally viable to the AI analytics, action, intelligence, and experience for the digital twin. From an economic perspective, digital twins enable low cost and high-fidelity manipulation for smart IIoT systems for a wide range of experiments. This reduces the cost of developing coarse-grained and asynchronous simulation, emulation, and testbed tools. The digital twin enables efficient and reliable management through resource scheduling algorithms to reduce operational costs. The digital twin also empowers rapid response and recovery, The DT-IIoT leverages the digital twin, as key strategic information technology, to empower the intelligence and security of IIoT systems. To systematically survey the existing research on the digital twin, we reviewed preliminaries, real world applications, and digital twin architecture and models.We investigated not only the classic machine learning solutions for prediction, classification, and automation problems of IIoT but also the state-of-the-art AI Solutions, such as transfer learning and federated learning. Besides, we investigated data security and control security issues, as well as state-of-the-art blockchain-based security solutions. Moreover, software tools for high-fidelity digital twin modelling are discussed. We conducted a case study on AI-driven DT-IIoT ,which consists of the CSTR process control system for validation and reinforcement learning-based integrated control and computing resource allocation. Finally, digital twin prospective applications, challenges, and integration with ABCDE are outlined which greatly reduces financial losses following a cyber attack or emergency scenario. From an intelligence perspective, the digital twin ensures adaptive resource allocation through AI algorithms with the massive amount of data in the digital twin. The digital twin simultaneously interacts with real-world smart IIoT systems to achieve self-awareness and evolution. In addition, the digital twin can be maintained predictively with AI algorithms.DT-IIoT has three security features such as risk assessment, security monitoring, remote diagnosis, and response. [5]

Digital Twin is as simple algorithm that forecast show a product or process will perform based on real world data.These applications incorporate the Internet of Things(IoT),Artificial Intelligence(AI),and data analytics to improve out put results.The digital twin frequently includes auxiliary data such as the device's firmware version, configuration, calibration, and set point data. By utilizing 3D simulations enhanced with augmented and virtual reality, engineers can streamline the product design process and eliminate numerous time-consuming steps typically required when developing a new product. Product specs, materials to be utilised, and how the design compare to key rules, standards, and laws may all be decided virtually before any materials are invested.Digital twin all engineers To discover any possible concerns with quality and viability before designs are completed, resulting insignificant cost savings. Data collected for Digital Twin can indicate when equipment maintenance is required and when failures will occur.Timely reporting these needs to human monitors may save businesses time and money and reduce downtime for essential repairs. The benefits of Digital Twin extend beyond the design process and into the product's lifespan.The twin can also answer critical issues regarding an asset's behaviour under stressors and varied environments. Data collection and analysis technologies ,such as edge computing hardware and IoT solutions ,are regularly implemented within facilities to execute a wide range of data-driven policies.The digital twin combines the data acquired by various technologies into a

Single virtual environment to reflect an industrial facility's precise and present operational condition.A digital twin provides a real- time virtual mirror of a company's production processes.Data-capture technologies supply the digital twin with real-time information on shop floor activities.The digital twin may improve present manufacturing performance and accelerate Industry4.0 Growth.It improves virtual testing and validation processes.Virtual testing for process validation is a crucial Industry4.0 idea since it lowers waste, minimises downtime, and educates factory-floor operators on new initiatives. Because of its capacity to map out industrial activities in real time, the digital twin is positioned as the ultimate validation tool.Industrial organisations can use the digital twin to assess strategies.Because the digital twin offers a virtualised environment and duplicates fundamental processes with great precision, it is a best-in-class validation tool because the impact so flim it scan be visualised and correctly studied without just numbers 'limitations.Digital Twin is virtual or digital representations of actual objects or processes.These digital representations are supplied With Real-time data gathered by sensors embedded within the target process and analyzed through AI algorithms. A virtual representation of a physical system that may also function as an independent entity.This digital replica Is a 'twin 'of information entrenched in the physical system in the same way as the physical elements are With the introduction of IoT ,a digital twin may continually gather sensor data and send information back and forth with the physical counter part throughout the system's lifecycle.Manufacturing processes, sensor input, and external managements of tware may all be fed into and organised Inside the digital twin.Digital Twin enables a complete representation of the manufacturing process, from a single component to the entire facility. Digital twin technology is destined to become a must-have tool for companies embarking on the Industry4.0 journey that wish to digitalise, optimise, and manage their factories in a smarter, more efficient manner.This technology is transforming the face of the industrial business, lowering costs, controlling assets, and reducing downtime caused by equipment failure. This opens up new opportunities for every firm throughout the world. The digital twin produces a high-complexity virtual model that is the counterpart/twin of a real entity. t uses actual data to estimate the capabilities of a process or a product. Parts twinning assists engineers and developers in better understanding a given part's mechanical, physical, and intellectual features in the context of the entire product.The twinning of working parts or interoperability twinning permits product twinning.It is a step up from individual element twinning.This ensures that all pieces are digitally represented and assembled functionally.[6]

In recent years, Digital Twin technology has gained considerable attention from both industry and academia. The term has been defined in various ways across different disciplines, as it is applied to distinct focus areas. Essentially, a Digital Twin refers to the seamless bidirectional data integration between a physical machine and its virtual counterpart. Initially, this technology was employed by NASA in the fields of astronautics and aerospace, notably during the Apollo 13 mission and the Mars Rover Curiosity project. In this paper, most of the Academic journal articles frequently explore the application of Digital Twin solutions in manufacturing, especially in relation to the principles of Industry 4.0. Research concerning Digital Twin solutions in manufacturing deals with production planning and control, which plays a central role in integrating all data within a production system. Supply chain management is another area where Digital Twin use cases are extensively discussed in the literature, with growing applications in the construction and healthcare industries. In construction, the Digital Twin concept, combined with mobile devices and wearables on-site, can provide a more accurate representation of the as-built environment compared to initial designs vs. the as-designed project at any given time. Additionally, Digital Twin technology helps reduce errors and rework by providing real-time updates that can be fed back to the field. In the healthcare sector, Digital Twin solutions are being used to identify emerging illnesses, test treatments, and enhance surgical preparation. By creating accurate, full-dimensional models of the human body, doctors can better detect early-stage diseases, experiment with treatment options, and refine surgical strategies. Researchers have made substantial progress in developing Digital Twins to analyze the human body, advancing the field significantly. Living Heart project is a common technology for clinical diagnosis, testing, medical device design, and education and training. Digital Twin solutions have led to the creation of highly accurate virtual models of human organs, incorporating factors such as blood flow, mechanics, and electrical activity. Advances in Artificial Intelligence (AI), the Internet of Things (IoT), and cloud computing have laid the foundation for the rapid evolution of Digital Twin technologies, enabling their application across diverse sectors including manufacturing, supply chains, life sciences, agriculture, and energy. AI, in particular, allows Digital Twins to simulate complex real-world systems by leveraging data from IoT devices to learn and operate in parallel with actual systems. This continuous analysis helps identify areas for improvement and supports strategic decision-making, while also optimizing system design to prevent costly redesigns during implementation.

The increasing demand for automation across various industries is expected to drive the growth of Digital Twin platforms in the coming years. As industries recover from the pandemic, Digital Twin solutions are set to become even more integral to sectors worldwide. While there are still challenges related to data quality, security, storage requirements, and integration with existing systems, the potential benefits of Digital Twin solutions remain vast and largely untapped. In the future, these solutions will expand into additional use cases and industries, integrating with technologies like augmented reality (AR) to provide immersive experiences, and AI to enhance connectivity, insights, and analytics. These advancements will offer deeper insights and open up new possibilities for Digital Twin applications in increasingly complex operations. [7]

The convergence of cloud computing, big data, Artificial Intelligence (AI), and the Internet of Things (IoT)—the four key drivers of digital transformation—has significantly accelerated the development and adoption of Digital Twins (DTs) across various industries. This paper presents a comprehensive and up-to-date survey of DT technologies, with a focus on their relevance and impact in the aerospace sector, particularly within manufacturing and operational domains. The origin and evolution of DTs are examined, highlighting their progression from conceptual models to integral components of industrial digitalization. Their gradual adoption in aerospace applications, including new product development (NPD) and operations and maintenance (O&M), is discussed in detail. With aircraft systems becoming increasingly complex and data-rich due to high-density onboard sensors and tightly interconnected subsystems, managing the vast, heterogeneous data sets generated in real-time has become a significant challenge. Efficient transfer, processing, and analysis of this data are essential to building high-fidelity aerospace Digital Twins (aero-DTs) for critical systems such as propulsion, landing gear, and avionics. When properly optimized, aero-DTs can offer substantial technical advantages in lifecycle management and predictive support.

Given the increasing importance of DTs in the aerospace domain, there is growing interest from both industry and academia. However, many practitioners still lack clarity regarding the classifications, enabling technologies, and practical deployment of DTs. This paper addresses this gap by categorizing and analyzing the key enabling technologies for aero-DTs, providing a structured overview to support informed decision-making. Notably, the current landscape lacks consensus on optimal technology choices—many developers rely on machine learning models without adequately considering the underlying physics of systems.

To ensure the development of effective aero-DTs, solutions must be tailored to specific operational and functional needs. The paper outlines common challenges—including limited domain-specific design knowledge, real-time data acquisition barriers, and integration issues—and proposes a strategic roadmap centered around three pillars: standardization, interactivity, and cognizance. If adopted effectively, this roadmap can empower the aerospace industry to elevate system performance, usability, and overall operational readiness.[8]

The concept of a Digital Twin (DT), though not novel, continues to evolve as a multidimensional technology framework. Initially introduced in the context of aerospace and advanced manufacturing, DTs have since expanded into diverse industries including healthcare, automotive, energy, and smart cities. Despite the widespread usage, the term "Digital Twin" lacks a globally standardized definition, as its implementation varies significantly based on application domain and technology stack.

A DT may rely on different model types ranging from high-fidelity physics-based simulations to data driven, AI-powered explainable models, or even hybrid configurations combining both paradigms. The growing availability of advanced technologies such as IoT, cloud computing, and AI has significantly enhanced the feasibility of building complex DT systems with integrated functionalities.

A widely accepted and structured conceptual model proposed by Tao et al. [2018] delineates five distinct components essential to modern DT implementations:

•Physical Entity (PE): The real-world object, system, or process being digitally mirrored. In aerospace, this may refer to components such as an aircraft engine, landing gear, or fuselage.

•Virtual Entity (VE): The digital counterpart that replicates the structure, behavior, and status of the physical entity. This entity evolves alongside its physical twin through continuous updates.

•Connection (CN): The bidirectional communication infrastructure—often realized via IoT and APIs—that facilitates seamless data exchange between the physical and virtual entities in real time.

•Digital Twin Data (DD): The structured repository of real-time and historical data generated through sensors, simulations, and analytics. It supports model accuracy and operational insights.

•Services (Ss): The intelligent functions that act upon the DD to deliver actionable outcomes such as diagnostics, predictive maintenance, optimization, and decision support.

These five components are underpinned by five enabling technologies—IoT, Cloud Computing (CC), Artificial Intelligence (AI), Application Programming Interfaces (APIs), and Extended Reality (XR) such as Augmented and Virtual Reality [Gesing, 2018]. Together, they form the technological backbone for the development of scalable and intelligent DT systems, particularly in complex domains like aerospace where precision, safety, and adaptability are critical.[9]

Digital Twin solutions have become increasingly vital in modern industries. As an evolution of the Internet of Things (IoT), Digital Twins replicate the planned production processes and gather real-time data via IoT sensors, enabling engineers to detect potential errors before production begins. This capability is critical for supporting the digital transformation across various sectors in line with the Industry 4.0 framework. However, the full potential of Digital Twin technology remains largely untapped. This paper aims to substantiate this observation through a systematic review focused on the aerospace industry, particularly aircraft maintenance processes.The results indicated a slight predominance of the data-driven approach, which emphasizes the services and benefits provided by Digital Twins, compared to the physics-based approach that focuses more on design and testing tools.The review also focused on aircraft subsystems utilizing Digital Twin technologies. Eleven specific aircraft components were analyzed, with no clear preference for either the modeling methodology or the subject matter. The insights gained led to the development of a modular architecture that represents the collective knowledge gathered from the reviewed works. This architecture is designed to capture the essential services and features highlighted in the literature and is structured as a set of independent modules involved in the process of creating Digital Twins for predictive aircraft maintenance.

Moreover, the study identified several open research areas requiring further exploration. These include Big Data, IoT, Edge Computing, the Digital Twin itself, and Deep Neural Networks. The most pressing issue identified was the inadequate IoT support for Digital Twins in predictive maintenance applications. To address this, our proposed modular architecture strengthens the role of IoT by adhering to architectural standards. Practically, this modular approach allows industry professionals, researchers, and experts to focus on specific components,enabling experimentation with alternative solutions and collaboration with stakeholders interested in different areas to contribute to the overall Digital Twin for aircraft maintenance.[10]

This paper presents a comprehensive framework for implementing digital twins in aircraft lifecycle management, with an emphasis on integrating data-driven models to enhance decision-making and operational efficiency. The proposed framework marks a significant advancement in aviation technology, providing a holistic approach to managing the complex lifecycle of modern aircraft. A key strength of the framework is its integration of advanced technologies such as IoT sensors, big data analytics, machine learning, 6G communication, and cloud computing. By harnessing these technologies, the digital twin ecosystem can offer real-time, accurate representations of aircraft throughout their operational life, addressing longstanding challenges in the aviation industry, particularly in maintaining up-to-date digital models during both operational and maintenance phases.

A major contribution of this work is the in-depth exploration of the framework's components, including the lifecycle phases, new technologies, and models for digital twins. The paper demonstrates how these elements work together to create a dynamic and adaptive digital representation of an aircraft that evolves to meet the changing conditions and needs throughout its lifecycle. The use of physics-based, data-driven, and hybrid models provides a solid foundation for simulating and predicting aircraft behavior under

different conditions. This multi-model approach ensures the digital twin can accurately reflect both established physical principles and the complex, data-driven patterns that emerge from real-world use.
Supporting components of the framework, such as data management, integration, federated learning, and analytics tools, ensure that the digital twin remains a practical and implementable solution. These elements address critical challenges related to data privacy, collaborative learning, and the generation of actionable insights from vast datasets. The paper also emphasizes the importance of decision-making models within the digital twin framework. By incorporating tools for predictive maintenance, operational optimization, and other decision support functions, the framework ensures that the insights generated can be effectively translated into actions that enhance aircraft safety, efficiency, and performance.
Furthermore, the paper introduces a knowledge-driven approach to digital twins, integrating diverse knowledge sources and utilizing semantic technologies to create more intelligent, context-aware digital twins. This approach paves the way for deeper insights and more refined decision-making capabilities. While acknowledging the significant potential of this framework, the paper also highlights challenges and limitations in implementing digital twins for aircraft. Issues such as data quality, integration complexity, scalability, and security remain critical areas for continued research and development. Nevertheless, the framework lays a strong foundation for realizing the full potential of digital twins, ultimately driving more efficient and reliable operations within the aviation industry. [11]
Exact and fast monitoring of the aircraft units could reduce the risk of jeo pardizing the passengers 'lives and decrease serious economic damages to aviation fleets.By applying DTs to the aviation units, the control, decision making, condition monitoring, and management of aircraft could be performed faster and more reliably compared to conventional monitoring methods. This paper aims to review the most important efforts in using DT for condition and fleet monitoring of aviation units. For this purpose, firstly, the introduction section proposes the necessity of using DT in aircraft conditions and fleet monitoring. the efforts and achievements related to using DT for aircraft systems have been analysed, and these studies have been categorized based on their virtual models that could be based on artificial intelligence techniques or conventional modelling methods. It should be mentioned that in future DT-based systems will play a critical role in condition monitoring of aircraft, with respect to growing trends in electrification, and digitalization of aircraft. In this regard, it should be stated that the future trends related to electric aircraft has been discussed in ''Future Trends ''section. Also, the future trends of DT-based systems have been discussed in this section. The future of electric aircraft tends towards the cryoelectrification of drivetrain where liquid hydrogen is used as fuel as well as the coolant of the superconducting devices. By having this combination, the hybrid electric aircraft is accessible. On the other hand, DT-based systems would take the participate more in monitoring, manufacturing, and maintenance of aircraft units that could reduce the risk of failures and crashes.[12]
The implementation of Digital Twins (DTs) in aviation manufacturing and Maintenance, Repair, and Overhaul (MRO) is challenged by numerous integration and organizational hurdles. One of the primary obstacles is the fragmented nature of stakeholders involved in the product lifecycle and life-extension services—each operating with its own legacy systems and unique process characteristics. This diversity has led to a variety of disparate data management solutions, making it difficult to achieve seamless integration into a unified DT framework using existing information systems. Furthermore, compliance and regulatory constraints often prevent even the basic connection of separate data silos or individual digital twins.

This study demonstrates that while complete integration into a single DT is currently impractical, it is feasible to aggregate and replicate specific, purpose-oriented data and domain-relevant information within standalone DTs. These domain-specific twins can support the optimization of isolated processes in development, planning, and production, as illustrated in various practical use cases. The next step toward unlocking greater value lies in interconnecting these individual DTs using standardized interfaces, thereby enabling collaborative engineering and better utilization of data for tasks like predictive maintenance.Ongoing research and development into DT applications for aircraft manufacturing highlight the scale of transformation still required. The aviation sector must invest considerable effort to digitally represent both physical and abstract elements within historically entrenched workflows.To address these challenges, emerging solutions such as federated learning models, independent data custodians, and initiatives like Gaia-X offer promising pathways to navigate compliance and integration difficulties.
Major players in the industry are actively pursuing digital transformation through initiatives such as Airbus's Digital Design, Manufacturing & Services (DDMS) and Lufthansa Technik's "Digitize the Core." These programs are not only implementing the outcomes of current research but also identifying new areas requiring further exploration. Notably, Lufthansa Technik has reported that they are engaged in hundreds of individual projects under this initiative, underscoring the industry's commitment to the digital future [13]

3. Methodology and Discussion

The concept of Digital Twins (DT) has found widespread application in the aviation industry, addressing both operational and manufacturing challenges. In the context of aircraft condition and fleet monitoring, DTs are leveraged to improve real-time diagnostics and predictive maintenance. This includes monitoring engine health, structural integrity, electrohydraulic actuators, and environmental control systems using data from sensors and simulation models like CFD (Computational Fluid Dynamics) and finite element analysis. Advanced methods like Artificial Intelligence (AI), including dynamic Bayesian neural networks and genetic algorithms, are employed to enhance prediction accuracy for fault detection, crack propagation, and remaining useful life of components. The aim is to reduce unexpected failures, enhance flight safety, and optimize maintenance intervals, particularly as aircraft systems move towards increased electrification and cryogenic propulsion using hydrogen. Digital Twins (DTs) represent the new generation of data carriers, transcending their early misconception as mere data collection tools. As illustrated in Figure 8, DTs facilitate bi-directional data flow through two-dimensional support. Horizontally, they maintain continuous data exchange across the entire product lifecycle spanning development, updates, and iterations. Vertically, they enable data mining, diagnostics, simulation, and predictive analysis at each node of the product. In addition to storing real-time operational data, DTs can also generate new data through virtual testing and performance forecasting. This integrated, dynamic data flow empowers enhanced decision-making and continuous product optimization.
The convergence of cloud computing, big data, Artificial Intelligence (AI), and the Internet of Things (IoT)—the four key drivers of digital transformation—has significantly accelerated the development and adoption of Digital Twins (DTs) across various industries. This paper presents a comprehensive and up-to-date survey of DT technologies, with a focus on their relevance and impact in the aerospace sector, particularly within manufacturing and operational domains. The origin and evolution of DTs are examined, highlighting their progression from conceptual models to integral components of industrial digitalization. Their gradual adoption in aerospace applications, including new product development

(NPD) and operations and maintenance (O&M), is discussed in detail. With aircraft systems becoming increasingly complex and data-rich due to high-density onboard sensors and tightly interconnected subsystems, managing the vast, heterogeneous data sets generated in real-time has become a significant challenge. Efficient transfer, processing, and analysis of this data are essential to building high-fidelity aerospace Digital Twins (aero-DTs) for critical systems such as propulsion, landing gear, and avionics. When properly optimized, aero-DTs can offer substantial technical advantages in lifecycle management and predictive support.

Given the increasing importance of DTs in the aerospace domain, there is growing interest from both industry and academia. However, many practitioners still lack clarity regarding the classifications, enabling technologies, and practical deployment of DTs. This paper addresses this gap by categorizing and analyzing the key enabling technologies for aero-DTs, providing a structured overview to support informed decision-making. Notably, the current landscape lacks consensus on
optimal

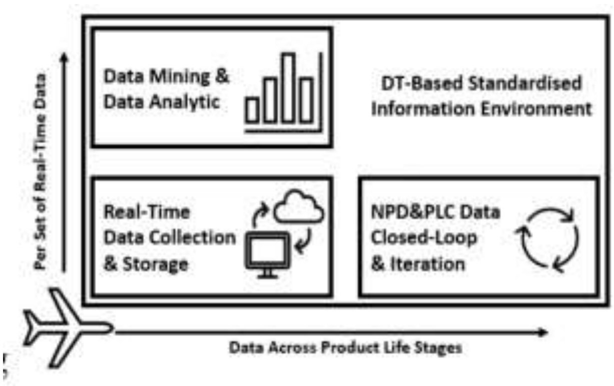

Fig. 3 Role of DTs in data science

technology choices—many developers rely on machine learning models without adequately considering the underlying physics

To ensure the development of effective aero-DTs, solutions must be tailored to specific operational and functional needs. The paper outlines common challenges—including limited domain-specific design knowledge, real-time data acquisition barriers, and integration issues—and proposes a strategic roadmap centered around three pillars: standardization, interactivity, and cognizance. If adopted effectively, this roadmap can empower the aerospace industry to elevate system performance, usability, and overall operational readiness.

1. Data Collection and Preprocessing

Historical sensor measurements from the Physical Entity Control System (PECS) are aggregated and cleaned to form a comprehensive dataset. Outliers and missing values are handled using standard imputation techniques to ensure full coverage of the system's operational range.

2.Data-Driven DT Model Training

A Random Forest regression model is trained on this historical dataset to learn the mapping between sensor inputs and key system outputs. Hyper parameters are optimized via cross-validation to maximize prediction accuracy across all operating conditions.

3.Real-Time Monitoring and Anomaly Detection

During operation, live sensor data is streamed to the ground station and fed into the trained Random Forest model. Predicted outputs are compared against actual measurements:
If prediction error remains below a predefined threshold, the system is classified as operating normally.
If error exceeds the threshold, an anomaly is flagged and localized to the specific component or subsystem branch exhibiting the greatest deviation.

4.Physics-Based Model Development

In parallel, a high-fidelity physics model of the PECS is constructed, incorporating the governing equations of fluid flow, thermodynamics, and mechanical dynamics. This model runs synchronously with the data-driven DT to:

- Cross-verify predictions and improve fault diagnosis confidence.
- Perform prognostics, generating future state projections and remaining useful life (RUL) estimates.
- Provide synthetic training data in regions where historical sensor coverage is sparse or unavailable.

5.Integrated Validation and Feedback Loop

Outputs from both models are continuously compared. Discrepancies trigger model recalibration: physics-driven insights guide additional training of the Random Forest in underrepresented regimes, while data-driven residuals inform refinement of the physics model parameters (see Fig. 4).

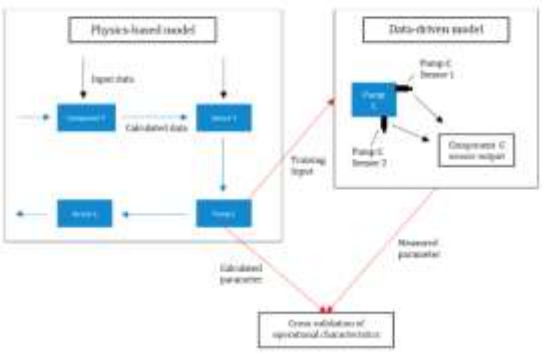

Fig. 4 Digital Twin: AI-based and Physics-based models

This dual-model approach leverages the strengths of both data-driven and physics-based paradigms to deliver robust, accurate, and self-improving Digital Twin functionality for the PECS.
The output data from the system can be utilized in two primary ways. First, it serves as input for training an AI-based, data-driven model—specifically, a Random Forest algorithm. This model learns the normal operational profile of the system and is capable of detecting anomalies by identifying data points that deviate from the learned baseline. In addition to fault detection, the model enables degradation monitoring of individual components by comparing real-time performance data against historical patterns of healthy operation. This facilitates accurate estimation of the component's Remaining Useful Life (RUL).
Second, the dense sensor instrumentation across the system provides high-resolution data that supports fault classification and localization. The spatial distribution of sensor feedback allows the model to isolate anomalies to specific components or branches of the system, enabling targeted maintenance and reducing diagnostic effort.
In this section, we build an example architecture for the proposed MDT concept by leveraging cloud computing and edge computing, enabling both real-time and bulk-batch ingestion, processing, and analytics of mobility data. As shown in Fig.3, the architecture can be divided into four layers:

Fig. 4 Example architecture of the proposed MDT with the cloud layer, edge layer, device layer, and API layer.

1. the cloud layer, which is built on AWS and its Virtual Private Cloud (VPC)
2. the edge layer, which has a computing component, a communication component, and a storage component
3. the device layer, which generates data and consumes guidance
4. the API (Application Programming Interface) layer, which hooks up the cloud layer with external APIs.

The major purpose of designing this architecture is to accommodate the proposed MDT framework shown in Fig. 4,so the Digital Twin does not just remain in the conceptual phase but can also be deployed in the real world with the help of cloud computing and edge computing. Particularly, the physical space of the MDT framework shown in Fig. 4 is represented by the device layer of this example architecture, where mobile apps, simulators, real vehicles and radio control (RC) vehicles sample data from Human, Vehicle and Traffic, and also actuate commands received from the edge and cloud layers. The communication plane of the MDT frame-work is positioned within the edge layer's communication component of this example architecture. The digital space of the MDT framework, along with its data lakes and microservices, spans the whole part of the cloud and API layers, as well as part of the edge layer (except for its communication component).

While both papers highlight the transformative potential of DTs, they also underscore significant challenges. Technically, integrating heterogeneous data sources (e.g., CAD, sensor streams, inspection logs) remains difficult due to the lack of standardized interfaces and semantics. Organizationally, the fragmented nature of the aviation ecosystem involving OEMs, suppliers, and MRO providers hinders seamless data sharing, especially given intellectual property and compliance constraints. Moreover, ensuring data security and regulatory alignment (e.g., EASA standards) complicates collaboration. From a modeling perspective, maintaining high-fidelity digital representations over the aircraft's lifespan is computationally intensive, especially when using real-time data. Lastly, scalability remains a hurdle, particularly when transitioning from component-level twins to full-system or factory-wide digital representations.

The application of DTs in aircraft production and MRO (Maintenance, Repair, and Overhaul) focuses on the optimization of the full aircraft lifecycle — from design and production to servicing and retrofitting. The implementation here is more process-oriented, targeting improvements in quality assurance, logistics, and manufacturing planning. Use cases include enabling flexible cabin assembly, streamlining production planning, automating quality checks, and integrating suppliers in a unified digital framework. The emphasis is on building Digital Masters and Digital Shadows that synchronize product data, production systems, and service procedures. This approach aims to reduce production inefficiencies, support co-customization, and improve traceability across globally distributed teams and facilities. Implementation steps:

1. Define System Architecture

a. Physical Space

- Aircraft sensors: Engine, avionics, hydraulics, flight controls
- Crew systems: Pilot biometrics (optional), flight deck interactions
- External data: Weather, ATC (air traffic control), airport systems

b. Digital Space (Cloud/Edge)

- Cloud platform: AWS, Azure, or private cloud (e.g., Airbus Skywise, Boeing AnalytX)
- Digital Twins:
- Aircraft Digital Twin (ADT)
- Pilot/Crew Digital Twin (CDT)
- Airspace/Environment Digital Twin (AST)

c. Communication Plane

- Protocols: ACARS, SATCOM, ADS-B, MQTT over VPN
- Mediums: Satellite, 5G (on-ground), Wi-Fi (in-flight when available)

2. Data Collection Layer (Onboard Device Layer) Implement:

- Flight data acquisition unit (FDAU)
- Edge computing hardware (e.g., NVIDIA Jetson, ARM Cortex)
- Data logging from:
- Engine sensors
- Navigation and control surfaces
- Cabin and pilot input devices

3. Edge Computing Layer Process data onboard for:

- Noise filtering
- Real-time alerting (e.g., anomaly detection)
- Temporary caching for intermittent connectivity

Tools:

- Docker containers on edge device
- Python or C++ for real-time analytics
- Redis for edge caching

4.Cloud Infrastructure Setup Deploy a 4-layer architecture (from the paper) on cloud:

1. Device Layer → Aircraft sensors & pilot inputs
2. Edge Layer → Onboard computers (low-latency tasks)
3. Cloud Layer → AWS/Azure (data lake, models, services)
4. API Layer → Interfaces to aviation databases, weather, etc.

AWS Example:

- Amazon S3 → Data lake
- Amazon EC2 or EMR → Machine learning models
- AWS IoT Core → Ingest real-time aircraft data

5. Develop Microservices for Each Digital Twin

a. Aircraft Digital Twin

- Predictive maintenance model using time-series data
- Example: LSTM or Random Forest on engine vibration

b. Crew Digital Twin

- Monitor pilot input rate, fatigue indicators
- Use biometric data if available (ECG, EEG from wearables)

c. Airspace Digital Twin

- Pull in traffic density, weather, and turbulence zones from APIs

- Use real-time simulation to suggest alternate paths

Step 6: Enable Feedback to Aircraft

- Send optimized commands or alerts back to cockpit
- “Potential turbulence ahead, suggest FL360”
- “Engine 2 shows vibration anomaly — land ASAP”
- Use AR HUD or EICAS integration for pilot interaction

Tools and Platforms

Cloud Platform: AWS, Azure, or Private Cloud
Edge Processing : NVIDIA Jetson, Raspberry Pi, ARM devices
Data Ingestion : MQTT, HTTPS, AWS IoT Core
Data Lake & ML : Amazon S3, Spark, SageMaker
Simulation & Testing: Unity, MATLAB, FlightGear, X-Plane

CONCLUSION

The integration of Digital Twin (DT) technology within the aviation sector marks a transformative shift in how aircraft systems are designed, monitored, and maintained. By enabling a seamless interplay between real-time data, virtual modeling, and advanced analytics, DTs offer unprecedented capabilities in predictive maintenance, fault detection, and lifecycle management. This paper has explored the conceptual foundations and technological enablers of DTs, alongside their evolution from early aerospace applications to their current role in Industry 4.0 ecosystems.

Through the convergence of enabling technologies such as IoT, AI, edge/cloud computing, and big data analytics, the DT framework has matured into a robust solution capable of delivering real-time operational insights and strategic value. The proposed architecture highlights how aircraft systems can benefit from modular, scalable, and adaptive DT deployments—supporting both tactical decision-making and long-term performance optimization.

Nevertheless, the path to full-scale implementation is not without challenges. Issues related to data integration, system interoperability, regulatory compliance, and model fidelity remain critical barriers. Future research should focus on refining hybrid AI-physics modeling, strengthening security and data governance, and standardizing DT interfaces across aerospace ecosystems.

Ultimately, the adoption of Digital Twins represents a critical step toward achieving autonomous, intelligent, and sustainable aviation operations. As electric and hydrogen-based propulsion technologies advance, DTs will play a pivotal role in ensuring the reliability and resilience of next-generation aircraft systems, propelling the aviation industry into a smarter, safer, and more connected future.

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