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TOPICAL REVIEW

Digital Twins for Condition and Fleet Monitoring of Aircraft: Toward More-Intelligent Electrified Aviation Systems

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ABSTRACT The convergence of Information Technology (IT), Operational Technology (OT), and Educational Technology (ET) has led to the emergence of the fourth industrial revolution. As a result, a new concept has emerged known as Digital Twins (DT), which is defined as "a virtual representation of various objects or systems that receive data from physical objects/systems to make changes and corrections". In the aviation industry, numerous attempts have been made to utilize DT in the design, manufacturing, and condition monitoring of aircraft fleets. Among these research efforts, real-time, accurate, fast, and predictive condition monitoring methods play a crucial role in ensuring the safe and efficient performance of aircraft. Using DT for condition and fleet monitoring not only enhances the reliability and safety of aircraft but also reduces operational and maintenance costs. In this paper, the conducted studies on the applications of DT systems for condition monitoring of aircraft units and the aerospace sector are discussed and reviewed. The aim of this review paper is to analyse the current developments of DT systems in the aviation industry as well as explain the remaining challenges of DT systems. Then Finally, future trends of DT systems along with aircraft are presented. Among reviewed papers, most of them have used computational fluid dynamics, finite element methods, and artificial intelligence techniques for developing DT models for aircraft. At the same time, most of these analyses are dedicated to the failure and crack detection body of aircraft as well as engine fault detection. Life prediction is another popular application for using DT in aircraft units that could help the engineers predict the maintenance required for different parts of the aircraft. Finally, the application of DT in marine, power systems, and space programs has been also reviewed and the lessons learned from them have been translated to the aviation sector.

INDEX TERMS Computational fluid dynamic, deep learning, machine learning, real-time condition monitoring, remaining useful life, structural health management.

I. INTRODUCTION

About 1900 annual aviation incidents were recorded in 1st decade of the 21st century [1] while it was reduced in recent years to about 1500 incidents per year that must be reduced further. As reported in [2], 49% of crashes are related to pilot error, 23% are related to mechanical failure, and the remaining 28% are caused by other reasons such as weather conditions, sabotage, bird strike, mid-air collision caused by other aircraft, overloaded aircraft, ground crew error, etc. As a result of this, condition, and fleet monitoring methods (CFMM) play a significant role in reducing the chance of fatal

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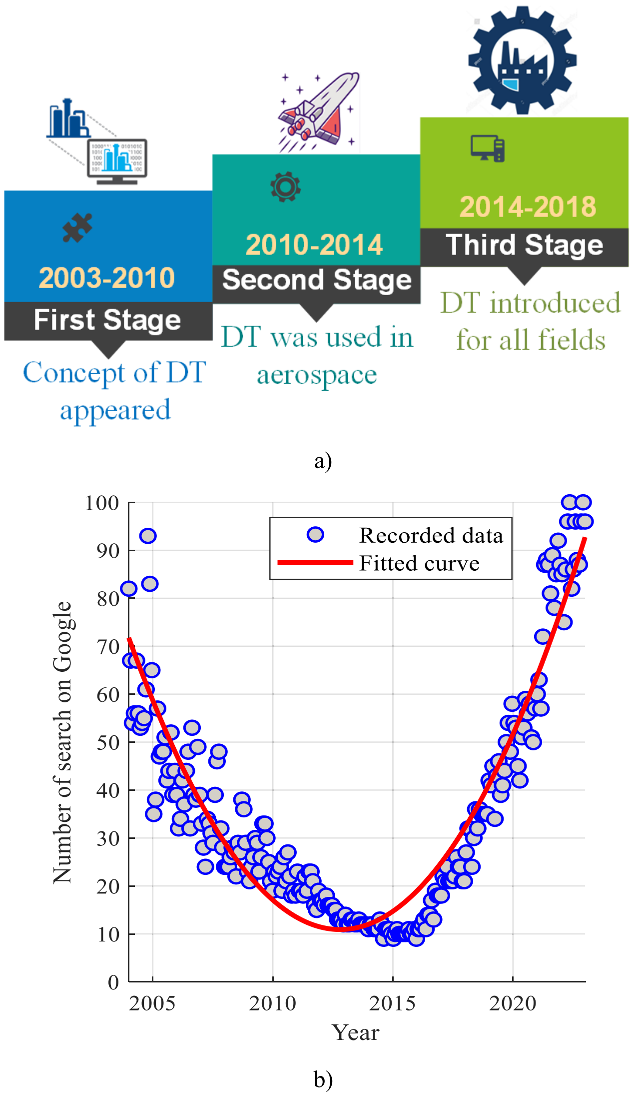

FIGURE 1. **The timeline of DT, from the beginning to present day, adapted from [3].**

crashes by managing engine failures, structural failures, fuel starvations, wrong take-offs and landings, aircraft control, navigation, etc. However, fatal crashes have still a high annual number and must be much decreased. This high number of incidents and crashes is because conventional CFMMs are usually based on time-consuming and sometimes methods with low accuracy that require the involvement of human operators.

Conventionally, condition monitoring of aviation units is divided into two main groups, on-flight methods, and off-flight methods. The on-flight condition monitoring methods usually use sensors and real-time data during the aircraft flight mission while human operators or Artificial Intelligence (AI) techniques are used for decision-making regarding the health management of the aircraft. The most common on-flight condition monitoring methods are:

- Engine health monitoring: in this method, sensors are used to measure temperature, pressure, vibration, and other critical parameters of aircraft to analyse engine health, detect anomalies, and predict coming failures [4], [5].
- Aircraft health and usage monitoring systems: this is a real-time method to monitor different components in aircraft, including engines, gearbox, wheel, structure, etc. The data gained by this method, during the flight, could be used for future off-flight predictive maintenances [6], [7].
- Structural health monitoring: for crack, fatigue, and damage detection purposes during the flight, sensors are used. Distributed sensing systems, wireless sensor networks, fibre optic sensors, and strain gauge sensors are the most conventional types for this purpose [7], [8].
- Oil debris monitoring: in this method, the oil samples are gathered online and analysed. Then, they are analysed for metal particles or contaminants which shows the potential problems in aircraft [9], [10].

On the other hand, off-flight methods are performed when the aircraft is in the airport or industrial maintenance site. Here, different techniques are used to detect cracks and malfunctions in the engine, structure, or electrical system of an aircraft. At this stage, the aircraft would be repaired and ready for the next flight. The most common off-flight condition monitoring methods are:

- Ultrasonic testing: high energy acoustic waves are generated through pulser -receiver and transducer, with a frequency ranging from 1 to 50 MHz. The aim of using this method is to detect flaws, identify their sizes, and estimate the material properties in presence of these flaws [11], [12].
- Magnetic particle inspection: for surface and near-surface flaw detection in ferromagnetic materials, this method is used. This method consists of following steps: component magnetization by direct current or electromagnetic induction, impose magnetic particles to the surface, and using a trained inspector for detecting the flaws [13], [14].
- Eddy current testing: To detect the flaws in electrically conducted materials, this method is used. In this method, a current is injected into the conductive material and the impedance is measured. Then, based on a correlation between current and the measured impedance, the type, location, size, and the existence of defect could be detected [15], [16].
- Photoelasticity testing: for visualization of stress distribution in different components of aircraft, optical effects of stress are investigated. However, because of its complexity, sensitivity, and technological advancements in other methods, photoelasticity tests are less common now [17], [18].
- Coin-tap method: this is the most well-known vibration test method where defect detection is conducted based

on differences between the sound of defected and non-defected zones. In this method, even the depth of the defect could be measured [68], [69].
- Radiographic inspection: This method involves the utilization of X-rays or gamma-rays. These waves penetrate the material and show the internal condition of the material and possible flaws. However, these methods are costly and time-consuming, and there are safety concerns about them [53], [70].
- Transient thermography: by feeding the energy heat into the test object and using thermal images of the test object's surface, it could be conceived that the defects create thermal impedance. Thus, this method could be used for the sake of defect detection in different components of aircraft [71], [72].

A comprehensive literature review on the comparison of different condition monitoring methods of aviation units is presented in Table 1 of the paper.

To find a compromise between accuracy, reliability, and speed of decision-making during the condition monitoring of aviation units, fundamental changes in conventional condition monitoring techniques are required. The aim of these changes should be optimal monitoring performance, reduced downtime of devices, providing continuous insights, and enabling predictive and prescriptive monitoring strategies. These requirements are what Digital Twins would be able to offer. Last recently and with the developments of Cyber-Physical Systems (CPS) [73], [74], [75], [76], [77], distributed computing [78], [79], [80], Artificial Intelligence (AI) methods [81], [82], [83], [84], [85], Internet of Things (IoT) [86], [87], [88], [89], and 5th and 6th generation (5G) and (6G) Internet [90], [91], [92], [93], in aircraft systems, CFMMs could be conducted faster, more accurate, and smarter, thus, the possibility of fatal incidents and crashes could be reduced.

According to Technology Roadmap, published by National Aeronautics and Space Administration (NASA), DT is defined as [94]: "*DT is a highly accurate simulation of an object, vehicle, or system that contains multiphysics, multiscale, and probabilistic models that gains the data and information from the sensors implemented in physical object and use them for control, design, condition monitoring, and manufacturing purposes of the physical object*". In 2014, Grieves introduced the concept of "*Digital twins*" in a white paper for production life cycle management [95]. After that NASA and the U.S. Airforce used DTs for many of their manufacturing processes, missions, etc. A brief history of DTs is shown in Figure 1, adapted from [3].

There is another concept, related to the DT, which is Digital Thread (DTH), which is defined as a data-driven structure that make the connection between different generated and stored information and data through DT, and let them be flown continuously. The aim of DTH is to integrate different data in one platform which results in seamless use and easy accessibility of the data. DTH is a process with multistep for the sake of complementation of DTs, over the entire lifecycle of the physical entity. It contains all the information necessary to generate and provide updates to a DT.

For further increase in accuracy, computational time, and decision-making procedures, all these concepts have been gathered into a new concept, known as Digital Twin (DT) [96], [97]. The concept of DT could significantly enhance the performance efficiency of CFMMs and further reduce the possibility of crashes in the future. The DT concept has been studied extensively and reviewed generally in literature for aviation sector [98], [99]. However, the lack of extended review on the application of DT for CFMM of aircraft and other aviation units is lacking. Therefore, this paper aims to present an extended review on the efforts conducted regarding the application of DT in CFMMs for aircraft. To do this, before delving into this topic, in section II of the paper, a brief introduction is provided on DT, cyber-physical systems, IoT (Internet of Things), and their common features. Then, sections III and IV involve with presenting the status and challenges in the aircraft industry, as well as challenges related to DTs and their associated infrastructures. Additionally, solutions for the application of DTs in the aviation industry are presented. In the section V, future trends in the aviation industry, such as electrified aircraft, hydrogen-based aircraft, etc., are discussed. Furthermore, the future of DTs and IoT is briefly explored.

It should be noted that the main contributions of this paper could be listed as follows:

- Reviewing the condition monitoring methods for aviation units, with respect to advantages and disadvantages.
- Introducing the concept of DT for aviation and reviewing the most important aspects of the DTs.
- Presenting the most important industrial projects regarding the applications of DTs in aviation sector.
- Reviewing more than 20 papers which present DT-based schemes for condition and health monitoring of aviation units and aircraft.
- Reviewing the papers in space, marine, and power system sectors that used DT for condition monitoring purposes. Then, tried to transmit their knowledge to the aviation sector.
- Presenting the challenges of DT implementation for aircraft, regarding their different aspects.
- Reviewing the future trends in electric aircraft, DT systems, and DT-electric-aircraft.

Methodology of Literature Review

The research conducted in this paper has been carried out based on a systematic literature review, based on what is proposed in [100]. The aim of this literature review is characterization of DTs for condition monitoring purposes. The data and information have been collected until the end of December 2023. For finding these information Google Scholar, and Google search engine have been reviewed and all papers, books, etc. have been stored. After gathering the data related to the application of DT for condition monitoring

TABLE 1. Review on condition monitoring methods in aviation units.

Method	Applications	Advantages	Disadvantages
Ultrasonic testing	* Structural health monitoring [19–23] * Defect detection aircraft cables [24–27] * Temperature monitoring [28]	High Sensitivity Depth Penetration Accurate Sizing and Location Real-time Inspection Non-Destructive Versatility Portability	Skill Dependent Surface Preparation Limited Accessibility Material Dependency Cost Coupland Requirement Thickness Limitations
Magnetic particle inspection	* Structural health monitoring [29–32] * Vibration control [33] * Engine monitoring [34]	High Sensitivity to Surface Flaws Fast and Cost-Effective Portable Equipment Versatility Immediate Results Minimal Surface Preparation Detects Both Surface and Subsurface Defects	Surface Accessibility Magnetic Properties Required Demagnetization Required Limited Sensitivity to Certain Defect Types Surface Finish Limitations Safety Concerns Training Required
Eddy current testing	* Structural health monitoring [35–41] * Aging monitoring [42,43]	High Sensitivity Rapid Inspection Non-Destructive Versatility Depth of Penetration Control Real-time Inspection Remote Inspection	Material Dependency Surface Finish Sensitivity Depth Limitation Complexity of Data Interpretation Equipment Sensitivity Cost of Equipment and Training Limited Detection Capability for Certain Defects
Photoelasticity testing	* Stress analysis [44] * Structural analysis [45–48]	Visualization of Stress Distribution Qualitative Analysis Non-Destructive Testing Real-time Observation High Sensitivity to Stress Changes Qualitative Comparison	Limited Quantitative Analysis Limited to Transparent Materials Complex Interpretation Limited Application in Aircraft Inspections Time and Equipment Requirements Environmental Limitations Incompatibility with Certain Materials and Loading Conditions
Coin-tap method	* Structural health monitoring [49–51]	Simplicity Low Cost Portability Rapid Screening Non-Destructive Sensitive to Delamination	Subjectivity Limited Sensitivity Surface Damage Risk Limited to Surface Inspection Inability to Quantify Defects Not Applicable to All Materials
Radiographic inspection	* Structural health monitoring [52–56] * Engine monitoring [57]	High Sensitivity Versatility Detection of Subsurface Defects Quantitative Analysis Permanent Record Non-Destructive Remote Inspection	Radiation Hazards Regulatory Compliance Equipment Complexity Environmental Impact Limited Accessibility Cost Processing Time
Transient thermography	* Structural health monitoring [58–67]	Rapid Inspection High Sensitivity Non-Contact Inspection Versatility Quantitative Analysis Real-Time Imaging Portable Equipment	Surface Preparation Depth Limitations Complexity of Analysis Environmental Factors Cost Training and Certification Limited Accessibility

of aircraft and other mentioned applications, the following research questions have been answered to form this paper.

A. What was the purpose of using DT?

B. Why the related research used DT instead of conventional methods of condition monitoring?

C. How DT was implemented in related research and what kind of modelling has been used for DT implementation, intelligent or conventional modelling?

D. What was the gap of the related research?

E. What was the lesson learned from the research.

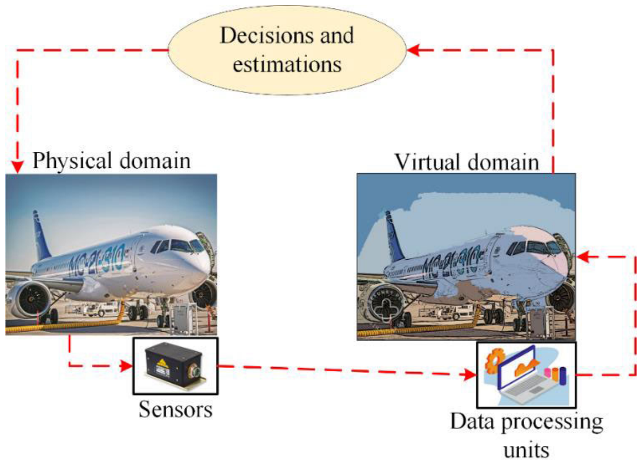

FIGURE 2. The illustration of a DT for an aircraft system.

II. DIGITAL TWINS: DEFINITION, HISTORY, AND APPLICATIONS

Although due to the variety of applications for DT, different definitions have been presented for them, all these definitions have three common characteristics, physical object, virtual models, and data-based connection of these two domains [101].

In an aircraft, the Digital Twin (DT) concept is illustrated in Figure 2, which comprises five crucial components: the physical domain, sensors, data processing units, virtual models, and data lines. Sensor units receive data, preprocess it by filtering out erroneous information and managing large datasets, and then transmit this data to the virtual domain/models. Within the virtual models, an analysis is conducted to make desired decisions or estimate required values. Subsequently, these decisions and estimations are sent back to the physical object to effect changes. These changes can pertain to the design or pre-design stages of the aircraft or can be used for monitoring the performance of the object or system. They may also be utilized to send a series of commands to manufacture machines or assembly lines. According to [102], each DT must have seven characteristics that are:

- ***High fidelity***: High fidelity means that DT must have an extremely high accuracy in performance, appearance, and subsystems. As a matter of fact, such accurate DT could help the designers, engineers, and operators to design, monitor, manufacture, and control the physical system/domain with high reliability and minimum possibility of failures.
- ***Dynamic and Self-evolving***: Since the physical domain/object changes with respect to time, the DT must have also the same characteristics and must be adapted with respect to the changes of the physical object. These changes could be in structure, characteristics, performance, or in control systems.
- ***Identifiable***: Each physical asset of an object or system must have its own specific DT to evolve and change over time. For instance, in an engine, the geometrical models, manufacturing models, monitoring models, estimation models, design models, etc. must be different and identifiable from each other. Thus, if there is a need to make changes in some part, just the related information is changed, and the rest remains constant.
- ***Multiscale and multi-physical:*** Each DT must be capable of concluding macroscopic properties such as shape size, tolerance, etc. and must conclude microscopic properties such as surface roughness or intermolecular forces. On the other hand, DTs ought to present all characteristics of physical objects such as thermal, electrical, mechanical, magnetic, economic, and their couplings. This capability is known as multi-physical and increases the accuracy and reliability of results.
- ***Multidisciplinary***: DTs are the fusion of multiple disciplines such as computer science, machine science, electric and electronic engineering, control engineering, mechanical engineering, and industrial engineering. This means that beyond each decision for a system, multiple considerations related to different disciplines are considered.

Hierarchical: DTs model different components of a whole system with different levels of priorities, concerns, limitations, and trade-offs. For instance, in an electric aircraft, there are different levels of DTs. DT of propulsion units, DT of engine units, DT of drive train, etc. Each one of these components comes with different priorities such as weight, safety, reliability, efficiency, and even temperature.

With respect to the last property of DT and according to [103], Figure 3 is presented as an example to show the different hierarchical levels of DT in an aircraft. The unit level of DT in an aircraft consists of materials, equipment, and components that together form a system such as propulsion, protection, drivetrain, etc. In the upper level, there are two types of systems, the whole system which is here an aircraft and all systems of an aircraft, known as the sum of subsystems. At the last level and the top layer, there is a DT that concerns the whole life cycle of an aircraft including, predesign, design, manufacture, control, monitoring, prediction, health management, disposal, etc. such as those conducted in [104], [105], [106], [107], [108], and [109].

DT has been used in many fields of industries such as power systems [110], [111], [112], [113], oil and gas energy systems [114], [115], healthcare sector [116], [117], [118], marine industry [119], [120], [121], smart cities [122], [123], [124], agriculture [125], [126], [127], environmental protection [128], and construction [129], [130], [131]. According to [132], the market of DT in the year 2020 was only about 3.1 BN and this value is predicted to be 48.2 BN in 2026. On the other hand, until the end of 2022, 75% of industries will be using IoT as a basic platform for DT [132]. The communication path initiates the existence of IoT to enable fast data/command transmission while for integrated calculation into physical assets, Cyber Physical Systems (CPS)

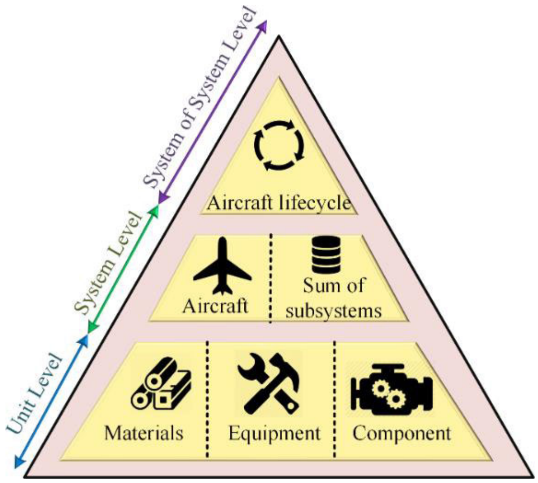

FIGURE 3. Different hierarchical levels of a DT for aircraft.

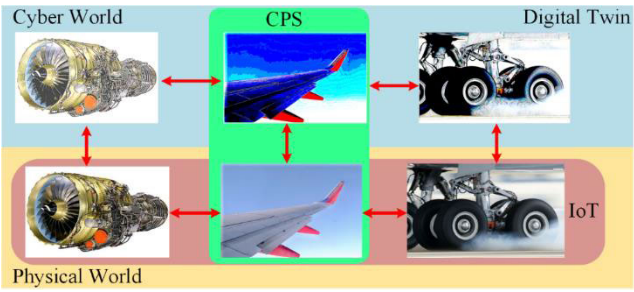

FIGURE 4. The correlation of CPS, IoT, and DT.

are required. Figure 4 presents the exact relation between IoT, CPS, and DT. CPS is defined as multiple computers connected to each other and interacting with the physical world through sensors, actuators, and feedback loops [133]. Reactive computation is one of the most important features of DTs that relies on asynchronous utilization of computational resources for a real-time and extremely fast response system. Another significant characteristic of CPS is concurrency which means using multiple computation strategies and processes at the same time to achieve a desired goal [134]. CPSs usually contain four layers, as shown in Figure 5. The first layer is related to the physical object which could be a component, the whole system, or even a series of systems. This layer sends the data and information to computation units to decide or apply the changes. The second layer is responsible for fast and real-time data/command transmission that receives the data from the physical layer and commands from the computation layer. This layer could consist of 5G internet stations, WiFi access points, or some sort of industry switches. The third layer is responsible for performing calculations, data management, and decision-making that must contain computers, data centres, and servers. Finally, there is a terminal layer that is responsible for executing or starting the whole process of CPS [135].

IoT is another term that must be defined that is used in the body of DTs to make data transmission faster and

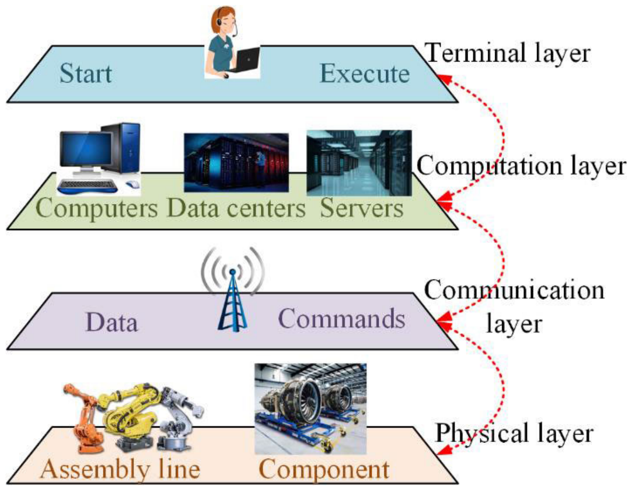

FIGURE 5. The layer-based structure of CPS, adapted from [134].

real-time. IoT is defined as "a dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual 'Things' have identities, physical attributes, and virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network" [136].

III. DIGITAL TWINS IN THE AVIATION INDUSTRY

A. LITERATURE REVIEW ON THE APPLICATION OF DT IN AIRCRAFT

The first steps of using DT in aviation systems started by NASA when it used DT to design maintenance strategies and malfunctions prediction in an aircraft, to reflect the real condition of aircraft. The utilized DT was able to optimize the performance of the aircraft, estimate faults in advance, and help operators understand the faults better and provide efficient solutions. In this regard, the U.S. Airforce dedicated a $20 million budget to research and develop a DT for F-35 fighters. The aim of using DT for the fighters was to improve manufacturing efficiency and reduce cost. An interesting point of this work is the utilization of a digital thread system for supporting the made decision, regarding unsatisfactory products which resulted in improvements of multiple engineering processes. Airbus also participated in the competition of DT application in aircraft, in 2011, where the A350XWB assembly line contained DT. This line participated in manufacturing many airplanes such as A330, A380, and A400M.

GKN Aerospace in partnership with General Electric (GE) and the Centre for Modelling & Simulation (CFMS) are investing on the development of a DT for their manufactured aircraft [137]. The aim is to reduce time inefficiencies and traditional physical prototyping costs [138]. Airbus has a wide digital transformation program to design, manufacture, and support the next generation of aircraft produced by Airbus. Also, the timeline of industrial production rates, operating performance of aircraft, and customer satisfaction would be increased by using DT, in the next generation of aircraft. It is estimated that the implementation of DT in A321XLR aircraft would 30% reduce the fuel burn. Also, the Future Combat Air System (FCAS) is another DT-based project of Airbus that would not only improve the defence technology of Europe but also will improve the spillovers into the civilian world [139]. German Airlines, Lufthansa, has developed a new DT-based project, known as AVIATAR which is an aircraft fleet using DT. The aim of this project is to use previous fleet management solutions, and data related to science and engineering to provide a full range of integrated digital services and products for its airline [140]. Boing is also using the DT for the digital design of the T-7A Red Hawk which is the first aircraft, satellites, and assets which are designed completely using DT-based methods. By using DT for this aircraft, the quality of the 1st product 75% while 80% of assembly time was reduced and finally, after 36 hours aircraft experienced its first flight mission [141]. Boing is also using DT for other products such as 737 MAX, 777X, and 787 for their production quality increase and digital life cycle assessment [142]. KLM, Royal Dutch Airlines, is another aerospace industry that uses 900,000 views of 104 DT to reduce the travel movements of crew, enhance the customers' services, and reduce the carbon footprint [143]. There are also other real-world projects on the application of DT in aviation units, such as the Northrop Grumman industry that is developing the DT for Bombardier CRJ700 [144], SAFRAN [145], and Honeywell [146].

It should be noted that conducted studies have been divided into two groups. The first group is related to the investigations and studies that used conventional modelling methods such as finite elements, equivalent circuits, etc. while the second group of studies have used artificial intelligence techniques for estimating and characterizing the behaviour/reaction of aircraft.

1) DIGITAL TWINS BASED ON CONVENTIONAL MODELING METHODS

The very high speed of aircraft in landing and take-off conditions and the level of stress on the tire could cause a phenomenon called a flat spot. Flat spots could result in wearing out of the tire and increase the possibility of the tire blowing up. To perform such a process, in [147], firstly experimental data of tire characteristics against ideal and non-ideal landing were acquired based on the performed tests on the tire in the United States Air Force 168-inch internal drum dynamometer (168i) and the aircraft 1 (A1). The performed experimental tests aimed to present different ranges of sink rate, tire profile, and yaw angles to increase the comprehensiveness of the tests. After that two methods (linear, and nonlinear) were used to calculate the touchdown wear response surface of the tires. Equations (1) and (2) express the relation between touchdowns wear response surface and sink rate, tire profile, and yaw angle for each linear and nonlinear method, respectively. where, SR is sink rate, TC is tire condition, θ_{Yaw} is yaw angle, C_i is constant value, P is pressure, $F_x(x)$ is drag force in x direction, and $F_Z(x)$ is drag force in Z direction. Thus, by accessing these models for the wear mechanism of tires, the DT process needs to be developed and implemented for A1 aircraft. To do this, firstly flight scenarios are considered and selected. After that, based on sink rate, tire condition, yaw angle, and touchdown speed, DT must calculate the touchdown wear response surface. After that probability of aircraft failure due to touch down is evaluated and based on the probability of aircraft failure and historical data the permission of the flight mission is published or cancelled. At last, after adding the field results of the mission, the DT model is updated according to flowchart Figure 6.

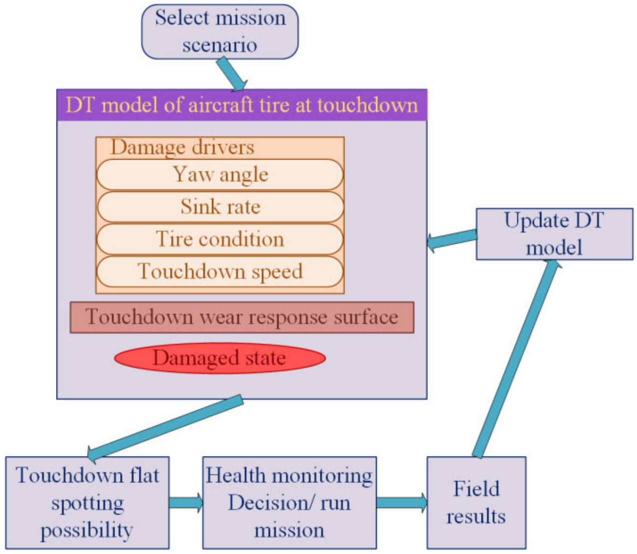

FIGURE 6. DT for tire health management in aircraft landing gear, adapted from [147].

$$TW_{LM} = C_1SR + C_2TC + C_3\theta_{Yaw} + C_4 \quad (1)$$

$$SWR_{flux} = A\int F_x(x)\frac{P}{F_Z(x)}dx \quad (2)$$

DT is used in [148] to increase the estimation accuracy and to reduce the prediction errors conducted for condition monitoring of a whole quadcopter with 3D printed frame, Pixhawk flight controller, NTM Prop Drive 28-36 750Kv motor, and APC Slow Flyer 10 × 4.7 propellers. Different models were used to characterize the performance of the quadcopter under different flight missions. The propeller system was modelled by blade element momentum theory [149] and the equivalent circuit model was used to characterize the operation of the brushless DC (BLDC) motor. BLDC motor is used in quadcopters to receive the DC power from the battery and propeller to provide the required rotational movements of the blades. By applying these models, the speed of the quadcopter was determined based on the weight of the device during the mission. The important aspect of this study was the fact that the proposed models for the propeller and electric motor were updated after each flight by changing the value of calibration factors. Calibration factors are a set of variables

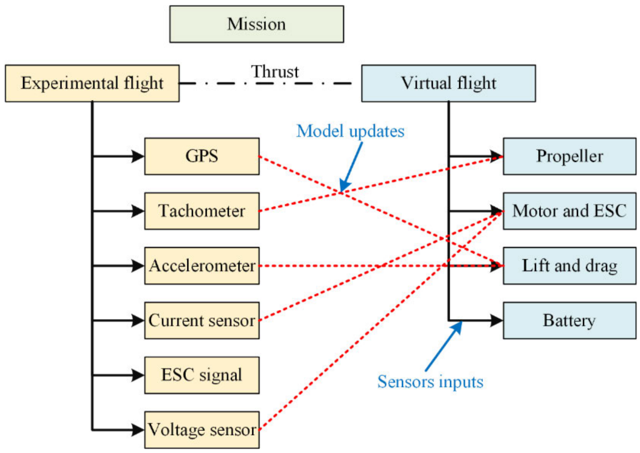

FIGURE 7. **The updating procedure of the models used in the virtual domain to monitor the condition of the quadcopter during missions [149].**

that were considered in related models of each component to make the characteristics of the virtual twin more like the physical twin. The diagram of such an updating process is illustrated in Figure 7.

Electrohydraulic servo-valves are usually modelled and simulated by means of FE-based computational fluid dynamics. The applications of such modelling methods for systems that require a fast solution are questionable [150]. To overcome this issue, in [151] a fast, adequately accurate, numerical, and semi-empirical formulation was presented to characterize the behaviour of the electrohydraulic actuator used in aircraft. The model was developed so that the real-time condition monitoring of the actuator system becomes conductible through DT. The proposed model used as a fast and accurate model of the actuator and valves is shown in the block diagram of Figure 8. In this figure, P_{SR} is the supply differential pressure, C_{LK} is leakage coefficient, G_p is the pressure gain, x_{SS} is the saturation spool displacement, x_S is the spool displacement, Q_J is the working flow, and G_Q is the flow gain. Also, in this model, actual differential pressure is calculated based on equation (3):

$$P_{12} = x_{S_t} \frac{P_{SR}}{\max\left(|x_S|, x_{SS}\right) + G_{PQ} C_{LK} x_{SS}} \tag{3}$$

where, the x_{S_t} is the equivalent spool displacement, and the G_{PQ} is the pressure to flow gain ratio. By applying this model, the root mean squared error (RMSE) of the predicted P_{12} was less than 0.1%. This means that the value of P_{12} was calculated with high accuracy and was in good agreement with the results of computational fluid dynamic analysis. As a result of this study, the proposed method was capable of being used as DT where a fast and real-time fluid dynamic computation was needed. As a further step, the ANN-based models could be also applied to further reduce the computation time while the accuracy can be maintained or even enhanced. The ANN models are capable of being adapted based on the requirements that one may have for fluid dynamic analysis.

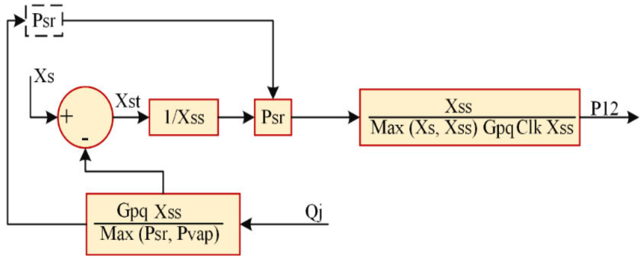

FIGURE 8. **The block diagram used to characterize the electrohydraulic behaviour of understudied actuator, adapted from [151].**

The ANN-based models could even adapt themselves to fit more to the flight conditions, based on their feedback loop.

The Environmental Control System (ECS) is obligated to control the airflow through the cabin of an aircraft that consist of multiple complex subsystems and procedures. Any failure in this system results in malfunction and inappropriate operation of the aircraft and reduces the required time for maintenance, known as unscheduled maintenance. The ECS depends on many flight conditions such as the weight of the aircraft, and weather conditions during flights, and it depends on many other factors such as type of manufacturing, type of materials used in aircraft, etc. [152]. In [153], a DT model was proposed to perform the ECS of any aircraft based on real-time/experimental data to avoid the consequences of ECS failure. The proposed method has three significant properties, i) the component-based library of the devices engaged in the ECS procedure, ii) the capability to model degradations of components, and iii) the inclusion of the environmental and weather conditions such as humidity in the ECS procedure. By applying such a smart ECS procedure, the impact of flight, manufacturing, and environmental conditions, known as experimental data, was considered in the ECS procedure of the B737-400 aircraft. Firstly, the data related to temperature, pressure, mass flow, valve angle, and efficiency are acquired. After that, the results and data are divided into two major groups, faulty data, and healthy ones. Then, in fault mode, the data are used to simulate the characteristics of different components to gain their degradation factor and after the fault detection in any of the subsystems, the used models would be updated. This procedure is shown for the whole ECS in Figure 9. The results of such DT implementation in B737-400 aircraft were discussed in three different cabin zones, cockpit, forward cabin, and aft cabin and for three different temperatures, 5oC, 18oC, and 30oC. After the simulation, the temperature and pressure for different components such as compressor, turbine, heat exchanges, air conditioner, etc. are obtained.

The cost of fuel that is used for running the engines of aircraft in addition to the manufacturing, repair, and overhaul (MRO) cost are the main sources of direct aircraft costs. All these considerations together define as engine fleet management, by cost optimization. To avoid complexities and reduce the risk of failures, in [154] a DT-based diagnosis and

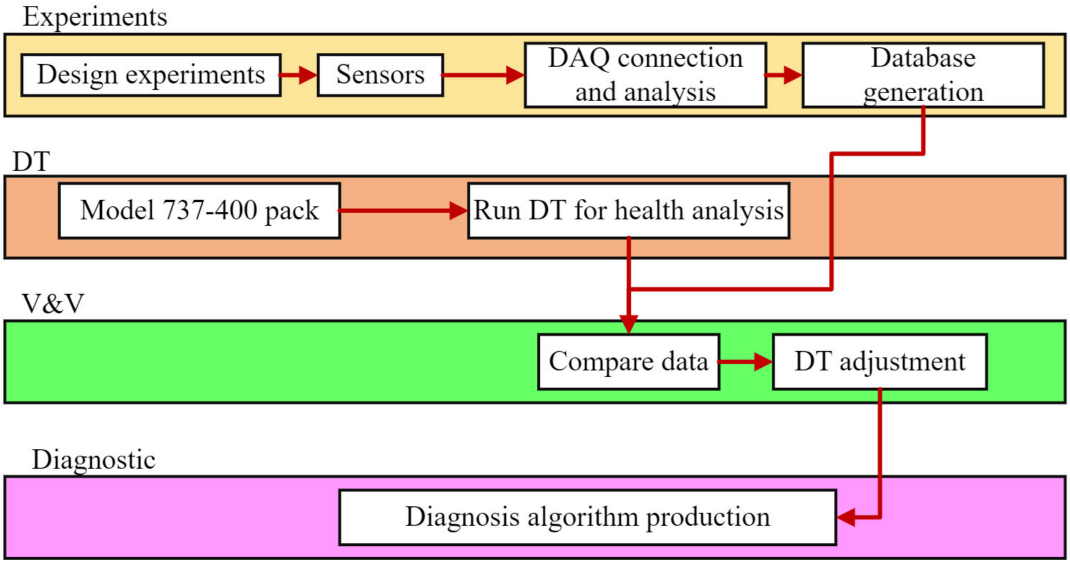

FIGURE 9. The ECS failure diagnosis procured by means of DTs in B737-400, Boing aircraft, adapted from [149].

prognosis method was proposed. The important part of this method was the provided multilevel model of the engine and its components and the DT was used to analyse the failures, predict the remaining useful life of all engine components, and change the engine working conditions based on the mission specifications. The fleet management data were updated based on the received information of the CFM56-5C commercialized engine of Airbus A340-300 aircraft. The DT consists of three sub-layers, at the first layer, a model for the engine cycle was adapted based on experimental and historical data. In this layer, based on the CFD method, the characteristic of different components of an understudied engine is discussed when they are under off-design conditions. The next and second layer of the DT model uses mean-line models to extend the components map beyond the areas that are difficult to reach and calculate by CDF. Finally, there is a third layer which is the library of CFD models of each component such as the Fan and Booster section, High Pressure Compressor (HPC), Combustion Chamber, and Turbine section. By applying such a DT-based model, parameters such as maximum temperature of booster versus HPC inlet temperature, temperature of high-pressure compressor, temperature distribution on blades, Mach number distribution, and cost of flight per engine flight hour are obtained. By accessing these values, the cost optimization of the engine could be done under realistic constraints and trade-offs. Again, the computation speed of the CFD method is questionable and due to the accessibility of data, the modelling in each layer could be conducted by AI techniques to reduce the computation time without loss of accuracy and generality.

MRO, as one of the most crucial steps in the aviation industry, includes heavy and difficult manual efforts that initiate challenges such as non-repeatable processes and low productivity. The MRO process of fan-blades is not excluded from challenges since the current grinding process is conducted manually by expert workers. Manual MRO of fan blades is a slow, difficult, and dangerous process that includes numerous grinding force parameters. To make this process simple and repeatable, reference [155] proposed an automated grinding procedure based on DT and robots for fan blades, as shown in Figure 10. By applying this method, the MRO could be conducted in a repeatable, simple, and automatic manner. As shown in Figure 10, the proposed method consists of four general steps. The very first step was the acquirement of the fan-blade condition during the grinding process by taking pictures with different methods such as hyper-spectral cameras, lasers, surface topography, and an RGB-D camera. The next step was known as the Markovian-based Surface Region Processor (MSRP) as an algorithm used for sensing the surface condition of fan-blade under grinding and to apply the appropriate grinding force. In the third stage, virtual particles for fan blades are generated based on the particle information resulting from the previous stage. Here, the physical surface of the fan blade was defined as the sum of particles in the Cartesian reference frame and then, the virtual particles were used to form a virtual surface of fan blade. Now, in the fourth step, the DT comes into play as the key stage of the automated MRO procedure. DT is used for four significant duties. The first duty is to consider grinding constraints and limitations such as surface roughness, generated heat during grinding, and prohibition of deteriorating the innermost composite layer of fan-blade. The next duty is calculating and presenting the grinding parameters such as the speed of the grinding wheel at each time step, material removal rate, wheel angle, and the maximum applied force to the surface. After the computation of grinding parameters, DT ought to model and characterize the fan blade in each time step to analyse the operability and health condition of the fan blade. At last, the whole control of the grinding process and the iterations that are needed for a completely reconditioned fan blade have been conducted by DT. Thus, the automated grinding process has been accomplished successfully and could enable a repeatable and simple grinding procedure. However, the performance and the condition of fan-blade that have gone through manual grinding must be compared to verify the privilege of this method. Also, economic considerations must be considered when comparing automated and manual grinding methods.

2) DATA-DRIVEN DIGITAL TWINS

The structural health monitoring (SHM) could help the decision makers to decide whether the aircraft can make another flight or needs to be repaired for the next mission. Due to variety of aircraft-related parameters such as different manufacturing methods, different material properties, mission conditions, etc., the SHM should not be conducted similarly based on information and data for all aircraft. The important aspect of SHM is that it is performed based on real-time and accurate data received by sensors of aircraft. Usually, the SHM is conducted based on pure-mathematical-physical models and systems that require a massive computation time and advanced computation resources [156], [157]. To overcome this issue, in [158], a dynamic Bayesian neural network (DBNN) was used to monitor the wing health condition of an aircraft. The DBNN is used for detecting crack growth on the leading edge of the wing as shown in Figure 11.

To fulfil the required task, four goals were aimed to be achieved, i) information homogenization ii) the flight of virtual aircraft with the same condition of the real one, iii) uncertainty reduction, and iv) predictive monitoring of cracks on the wing. To achieve these goals, DBNN was used as a promising technique that can model all uncertainties, and information inhomogeneity by using different types of random variables such as discrete and continuous variables belonging to different probabilistic distributions. Numerous uncertainties were modelled by DBNN such as those that exist in finite element (FE) methods, those related to crack growth characteristics, load uncertainty, and crack length data uncertainty. Thus, and by considering these uncertainties, the inputs of the DBNN are selected to be load, bolt looseness, anchor point position, stress range, elastic/plastic zones, crack length before the current time step, stress intensity factor, crack characteristic in current time, geometric and material properties, and shape factor in plastic zone. After implementation of such DBNN, and for 10000 time-steps with different loadings, the length of the crack and its rate of growth resulted that could help the diagnosis and prognosis of the health condition of the wing. This model can be used also for health monitoring of all structural and non-structural parts of the aircraft which could be the aim of future research. As the next step, a comparison needs to be performed for different aircraft with different flight conditions, different sensors, and different geometrical and material properties to show how theses parameters may change the diagnosis and prognosis results. Finally, one other uncertainty could be added to the model to increase the accuracy and efficiency of the model which is the probability of data loss during measurement and transmission.

Another application of DTs for SHM was presented in [159] that uses Guided Wave Response (GWR), Finite Element (FE) method, and Genetic Algorithm (GA) to detect the cracks at the body of aircraft. FE analysis is conducted on 2024-T3 aluminium plates to investigate their dynamic characteristics under different aerodynamic loads by means of Abaqus®/Explicit. These aluminium plates are 300 mm in height, 150 mm in width, and 1 mm thick while five and a half-cycle Hanning-window excitation signal with 50 kHz frequency is applied to these plates to perform the frequency analysis. Afterwards, to avoid the model inaccuracies and extremely long simulation times, the maximum time-step must be calculated for FE analysis as expressed in equation (4):

$$\Delta t_{max} = \frac{1}{20 f_{max}} \tag{4}$$

where, f_{max} is the maximum frequency in which simulations are going to be performed.

The next step is using the GA optimization method to characterize and predict the crack behaviour based on four variables, namely X_r and Y_r which show the crack centre location, crack size $2a_r$, and θ_r which defines the orientation of crack. Firstly, based on four variables, an arbitrary location and size is considered for the damage or crack and an FE is built based on the arbitrary crack. After that, a wave propagation analysis (WPA) is conducted to calculate the response of all N sensors installed at the understudied region. Then, the objective error function, shown in equation (5), is calculated to determine the accuracy of the predicted crack location.

$$\emptyset = \left[\sum_{i=1}^{N} \left(E_{sdc} - S_{sdc} \right)^2 \right]^{\frac{1}{2}} \tag{5}$$

where, E_{sdc} is the reference response related to the real crack while S_{sdc} is the calculated response. If the objective function is higher than relative tolerance, a new location is dedicated for crack and previous iterations would repeat until the convergence terms are fulfilled.

Three different case studies are defined to assess the capability of the proposed method for different crack locations, near sensors, near actuator, and between actuator and sensor. The results show the coordination of the crack could be estimated with 1% to 7% error for different case studies, while this value for size of the crack is about 2% to 8% and for crack orientation is about 3% to 9%.

Another objective of using DT is to predict the physical behaviour of different components based on the historical data and information of the simulations. For this purpose, in [160] and [161], a data-driven model was created based on the values of sensors. The proposed method offers a

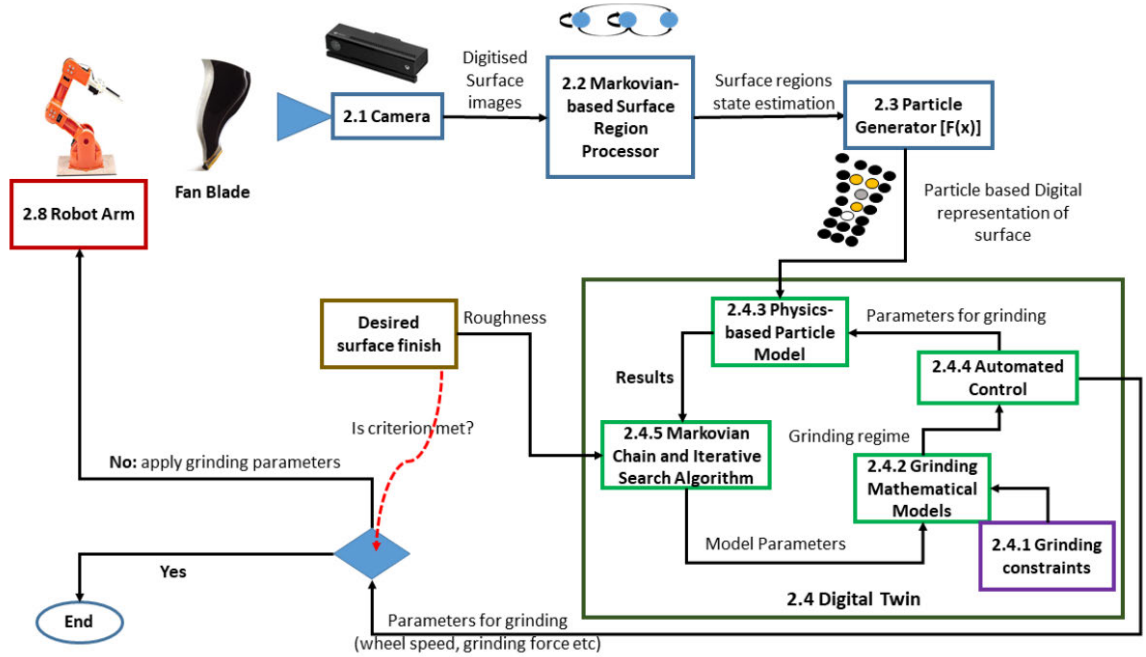

FIGURE 10. **The automated MRO process of fan-blades based on DTs and robots, adapted from [155].**

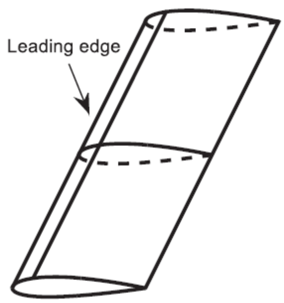

FIGURE 11. **The area of crack growth detection proposed by [158].**

solution to the problem of updating the model in the virtual domain. The proposed method was tested for a 12ft wingspan unmanned aerial vehicle. For this vehicle, the DT models of different components were created based on reduced-order FE analysis. After manufacturing the real twin of the aircraft and implementing the sensors, an FE-based model was created by Akselos Integra modelling software [162], to detect the health changes in the structure of the aircraft. After the simulation results those sensors', data were fed into a machine-learning model to update the data-driven model based on flight mission conditions. As a result of applying such a model, the DT re-plans the flight mission based on the received data of the structural damage so that the lowest aerodynamic load is applied to the damaged region of the aircraft. However, one needs to consider proposing a DT model that not only predicts the characteristics of the aircraft but also can consider all uncertainties in in-flight mission conditions, in characteristics of materials, in abrupt failure of engines, etc.

The proactive and predictive maintenance methods are now replacing the reactive methods, especially in aerospace applications. This is because these methods reduce the maintenance cost and downtime of aircraft while their lifetime, safety, and productivity are enhanced [163], [164]. Using DTs for this purpose not only increases the prediction accuracy and reduces the possibility of aircraft failures but also could end up with a solid prediction method that is updated based on the information of the flight mission for a specific type of aircraft [165]. For this purpose, in [166], a DT concept based on Bayesian interference was used to predict the structure life of an aircraft. To do this, two important efforts were conducted, firstly, the Bayesian interference method was implemented that could integrate all heterogeneous data which originate in FE methods, historical data, and data received by sensors and use them to predict the remaining useful life of aircraft body. Secondly, a discussion was also added to the paper that illustrated the implementation procedure of the proposed method into a real-time DT. For this purpose, the followings are fed into the DT as inputs to predict the remaining life of the aircraft body, i) load conditions such as aerodynamic pressure and ground loads that could result in cracks and holes, ii) material properties such as Poisson ratio and Young's modulus, the geometry of the aircraft to be used in FE method, iii) historical data of flight mission of the aircraft in same class, and iv) pre-defined failure threshold. Based on Paris law [167] and by using the flowchart of Figure 12, crack detection and remaining useful life prediction could be conducted. After applying this method to two case studies, the results shown that the predicted/calculated results follow the same trend of the real data of remaining useful life,

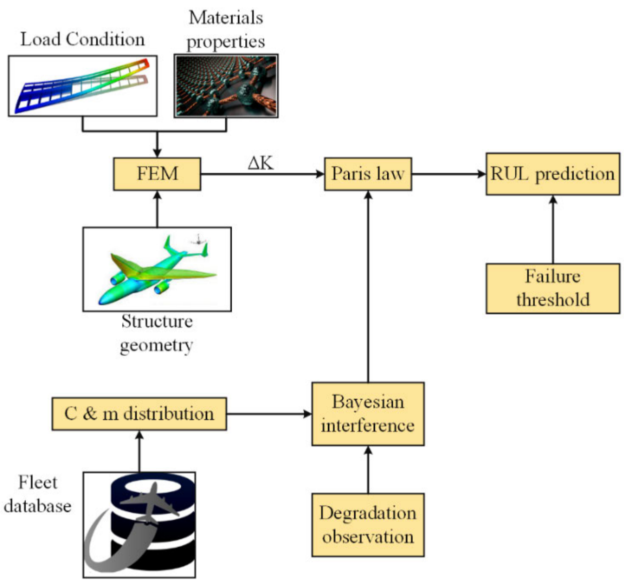

FIGURE 12. The crack detection and remaining useful life prediction procedure in structure of an aircraft, adapted from [166].

as show in Figure 13. Although the trend of the predicted values is in very good agreement with real values, the point-to-point accuracy could be further increased by application of artificial intelligence methods. These methods could replace the Bayesian interference system, Paris law, and FE method to increase the accuracy, computation speed, and adaptability of the prediction method. Also, Individual Aircraft Tracking (IAT) programs are one of the most important components of DT-based condition monitoring systems in aircraft. IAT programs aim to detect and predict the possible crack growth in an under-observation area of aircraft structure to avoid any crashes of aircraft. In [166], the IAT program for crack detection in F-16 aircraft is presented and compared with other crack detection methods to show the importance of application of a real-time and adaptable structural monitoring method. For the sake of applying an IAT program at F-16, these aircraft are equipped to flight-data recording systems of multiple types such as Flight Loads Recorder, Mechanical Strain Recorder, Crash Survival Flight Data Recorder, and Crash Survivable Memory Unit. These devices could be used in combination with the proposed method of [166] to increase the accuracy, computation time, and adaptability of the predictions. As discussed before, preventive maintenance is an important step to ensure the safe operation and performance of aircraft units.

In [168], a novel method was proposed for aero-engine preventive maintenance, the term ''aero-engine'' is defined as the engines of military aircraft with high thrust that offer a sudden climb and high ''G'' loads during manoeuvre, as defined in [169]. The proposed model is identified based on the historical data of aircraft operation and maintenance information of engines. In this regard, it should be mentioned that by applying such a method protective operation of aero-engine and health management of understudied engine is accessible. To do this, a model consisting of four sub-models was proposed which are data driven model (DDM), multi-parameter asset mapping (MPAM), model verification (MV), and deep learning-based model (DLM). In DDM, three important tasks are completed, firstly data is collected from sensors and after that bad data and noises are removed and time or frequency conversion are done. At last, parameters and features of data are extracted. After that the data is shared to MPAM phase, that is the stage in which DT is applied. In this stage, information of operation, maintenance, and the device information are used to accurately simulate the characteristic of aeroengine in a virtual space. After that the real results and the simulated ones are compared in MV phase to make sure that DT is performing with the highest possible accuracy. Lastly, a long short-term memory (LSTM) neural network is used to train a model with the capability of predicting any requirement for maintenance. The proposed model has a high accuracy in predicting the required maintenance in comparison to other methods such as K-nearest neighbors (KNN), deep convolutional neural networks, catBoost, and generative adversarial networks. The RMSE value of the proposed method is about 13.12 while this value for methods is about 20.46, 18.5, 16.91, and 15.8, respectively. The reduction of RMSE value shows that the predicted values for maintenance time are more trustable and increase the reliability of the aeroengine.

Unmanned aircraft systems use UAVs as their main components for numerous goals such as defence, traffic control, security of cities, and for plant protection in agricultural systems. The data acquired by UAVs and during a flight mission are transmitted through the internet to ground control units and after that commands and control decisions are made in these ground units and again transfer to the UAVs through internet. Then, these commands are sent to the physical equipment of UAVs to make the desired change or perform the required tasks. The interaction of internet, control systems, and physical elements of UAVs offers a high opportunity for taking the advantages of DTs for control, protection, and commanding the UAVS, as proposed by [170]. According to [170], an airspace is divided into flight information area, control area, restricted area, dangerous area, flight restricted area, and routes. In [170], the combination of Convolutional Neural Network (CNN), autonomous wireless network, and DTs was used for safe performance of UAVs inside the non-restricted and non-dangerous zones. In other words, by doing this, no UAV can enter the safe flight zone of other UAVs and other aircraft and the safe flight of UAV was guaranteed by considering the obstacles, routes, etc. As illustrated in Figure 14, the safe zone of aircraft Ai is a circle around its current position and when another aircraft enters this safe zone, the Ai must have sufficient time to react to this and modify its path. Here, CNNs receives the flight data of an aircraft through the wireless communication system and based on pre-defined rules and historical data, modifies the route of the aircraft, and sends the information

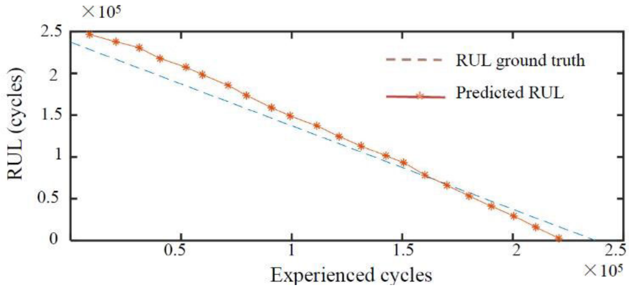

FIGURE 13. The predicted remaining life by the Bayesian interference system versus the real values, adapted from [166].

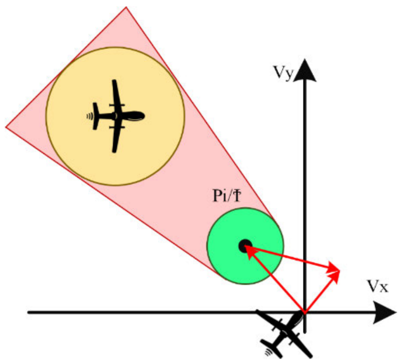

FIGURE 14. The conflict areal model that DTs are used to solve, adapted from [170].

of the new route back to the aircraft. Although the proposed method was very novel and capable of controlling the AI so that it can fly safely and without any possible crashes, there are some considerations to make. One of them is the fact that all safety zones of aircraft are non-identical, and an index needs to be defined to clarify different safety zones for different aircraft. Also, the impact of air traffic and other airspace limitations must be considered to make this method applicable, especially for manned aircraft where any failure results in catastrophes.

Another consideration of the fleet management process is exact and accurate fault/failure detection that can jeopardize the optimal fuel consumption. The most challenging issue of such a detection process is the large number of data that needs to be processed and the different types of engines that necessitate models which could be adapted based on these differences in engine structure. To overcome these issues, in [171] a DT-based diagnosis and health management system was proposed that consists of multiple stages. The first stage is dedicated to abnormality detection and failure quantification, the next stage is about physic-based simulations according to the Monte Carlo model, and the last stage is related to the data-driven models of engines. To perform the fault diagnosis stage, firstly, the engine's data are collected and fed into the algorithm, as shown in Figure 15, however, the gathered data must be corrected and normalized before the diagnosis process is initiated. The correction and normalization process are conducted based on

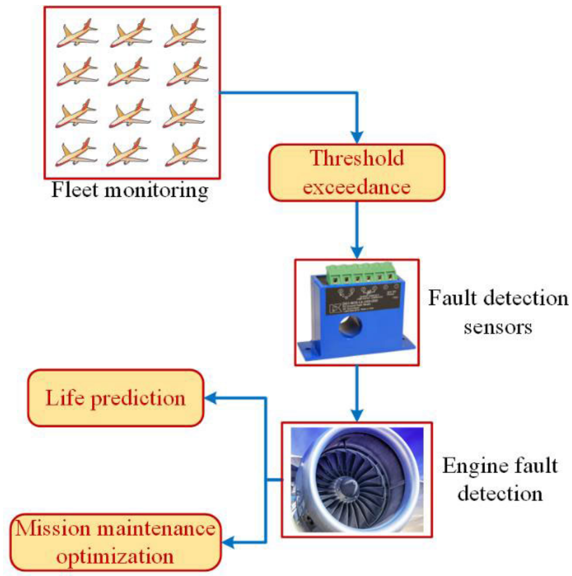

FIGURE 15. Fault diagnosis and engine isolation algorithm based on.

the healthy condition of a specific or baseline engine. The whole process is discussed in detail in [172]. Afterwards, the corrected data are compared with the expected value of a healthy engine and if their differences exceed a threshold value, the abnormality/fault in the engine is probable and thus, the faulty engine is isolated. In the next stage, the fault signatures reproduction of engine components is conducted by using the DT of the engine. After that, for each signature, a correlation the function is dedicated and the component with the highest value of the correlation function is isolated. It must be noted that to increase the accuracy of the engine DT, 1000 different case studies with different efficiencies and flow capacities are considered based on Monte Carlo simulations. This procedure was applied to the engines of a fleet in two manners. In the first approach, the data is normalized according to a baseline engine and in the second one, the data is normalized based on the specific engine of the fleet. In the first approach, only 5% of faults are detected correctly while this value for the second approach is 98.2%. This reference has also taken advantage of ANNs to classify the faults with a surprising result in fault detection. If ANNs are used based on the first approach, 57.4% of faults are classified and detected correctly while this value for the second approach is 100% which means all faults and abnormalities are detected and classified correctly.

Table 2 shows a summary of the most important conducted efforts regarding the application of DT for condition monitoring of aircraft and other aviation units.

B. LESSONS LEARNED BY OTHER INDUSTRIES

In [173], a novel fault diagnosis method based on DT was proposed for rotating machinery that suffers a fault in the rotor side. The first part of the DT is the real-time and experimental data that is received by smart sensors. Then,

TABLE 2. A summary of the most important studies on the utilization of DT in aviation units.

Reference	Type of study	Modelling method
[140]	Flat spot analysis of aircraft wheel	Analytical modelling
[148]	Structural condition monitoring	Element momentum theory
[149]	Engine condition monitoring	Circuit modelling
[151]	Servo-valves analysis	Semi-empirical method
[153]	Environmental control system	Numerical modelling
[154]	Engine failure analysis	Computational fluid dynamics
[155]	Manufacturing, repair, and overhaul analysis of fan blades	Markovian-based surface region process
[158]	Structural health monitoring	Dynamic Bayesian neural network
[159]	Structural health monitoring	Finite element and genetic algorithm
[160], [161]	Aircraft components characterization	Reduced-order FE analysis
[163], [164]	Crack detection	Finite element
[166]	Proactive and predictive maintenance	Bayesian interference method
[168]	preventive maintenance	Long short-term memory (LSTM) neural network
[170]	UAV control	Convolutional neural network
[171]	Optimal fuel consumption analysis	Monte Carlo model

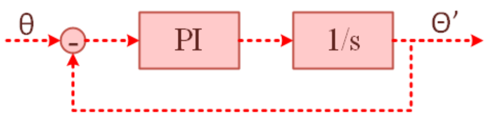

FIGURE 16. The control loop for noise filtering of sensed signals, adapted from [174].

there is an analytical model that is used to simulate the behaviour of rotating machines under different conditions. Finally, a particle swarm optimization method is used to minimize the error between the simulation data and experimental data. The most important feature of this method is the capability of modelling uncertainties and nonlinear dynamics of the rotor. The proposed model could be used in the same manner for fault diagnosis of aircraft engines. However, under such circumstances, there is a need for restructuring the DT model and the model of electrical machines to cope with the mechanical engines of aircraft. Another fault detection method based on real-time DT for a 1.8 kW and 208 V wound rotor induction machine is proposed in [174]. The significant aspect of the proposed model that can be used for aircraft and aviation industry, is the filtering procedure of data noises. The block diagram of Figure 16 is used to filter the noises of signals with a transfer function of equation (6).

In Figure 16, θ is the noisy signal, $\hat{\theta}$ is the filtered signal, and in equation (6) K_p is the gain of the proportional (P) controller and K_i is the gain of integral (I) controller. By applying such DTs, proposed by [171] formulation, the condition monitoring of aircraft could be conducted based on more accurate data and because of this the performance of the condition monitoring method would be improved.

A DT-based algorithm for fault detection and identification of photovoltaic (PV) systems has been proposed in [175] that enables the protection of PV units and control of the related power converters. At the fault detection part, the aim is to reduce the error between measured outputs and estimated outputs of the whole system. To do this, a threshold value is defined to enable the model to detect the faulty condition out of a normal operational mode. On the other hand, the type of fault must be also identified by taking three important steps, residual analysis for fault signatures, fault signature calculations, and fault identification logic. As a result of these steps along with the previous one, the fault could be detected in the body of PV units and the type of fault is identified to make a reliable protection decision. The very same methodology could be used in the aircraft system for two purposes, fault detection in different parts of the aircraft such as engine, structure, electrical system, etc. and to make the appropriate choices for protection of the aircraft against these faults and abnormalities. Also, deep learning-based DTs can be used as fault detectors in aircraft and other aviation systems, especially future electric aircraft, as one is proposed for fault detection of smart grids [176].

$$H(s) = \frac{K_p s + K_i}{s^2 + K_p s + K_i} \tag{6}$$

A novel condition monitoring method based on finite element method (FEM) and ANNs has been proposed in [177] for ship hull structures to locate the damaged part of the ship structure. To do this with FEM, firstly the strain values of the whole structure are acquired from the sensors and after that, a random guess is made on the position of the damage. After that FEM is used to gain the Von-Misses stress distribution and then the value of Von-Misses stress is fed into an error function. By minimization of the error function, the exact location of structural damage can be located, the minimization process is conducted in this paper by means of NSGA II. After the FEM is used, the outputs of FEM-based simulations train the ANNs. ANNs are used to detect the damaged side of the structure and are used to gain the damaged location. The very same methodology can be used also as SHM methods of aircraft to increase the computation speed of the damage location process. By implementation of the proposed method, the whole body of aircraft could be analysed to locate any possible damage on its body, in a fast, reliable, and real-time manner. To do this, some justifications on the properties of structural materials, the geometry of the problem, mission conditions and considerations, and the basic FEM is required. Another application of DTs in the marine industry has been offered by [178] ANNs to predict the combustion behaviour of propulsion engines. For this purpose, different components of propulsion systems such as air compressors, cylinder units, fuel pumps, propeller shafts, etc. are modelled through thermal, dynamic, and mechanical equations and the final output is used as the input to the ANN model. This can be also used in propulsion units of aircraft while just related equations to the aircraft dynamic must be changed, and concerns related to the aircraft must replace the limitations of ships. Another application of DTs has been presented in [179] to control the quality of the critical components of ships during manufacturing. The very same method can be also used in aircraft manufacturing, maintenance, and overhaul stages to reduce the risk of failures and crashes during flight missions.

DT has been used in [180] for analysing and evaluating the State of Charge (SOC) and State of Health (SOH) of lithium-ion batteries used in spacecraft. These battery packs are important components in any spacecraft and their performance degradation must be analysed in real-time to enable the power management of the spacecraft. To do this, a general algorithm has been used, as shown in Figure 17, for both SOC and SOH. The SOC is analysed by using Kalman Filter - Least Squares Support Vector Machine (KFLSSVM) and SOH is analysed through Auto Regression Model-Particle Filter (ARMPF). The very same algorithm could be used for the health management of engines in aircraft systems as a replacement for the SOH problem while the other method that has been used for SOC of the battery pack could be used as the electrical power manager inside the cabin. Another SOH monitoring method based on DTs and satellites is presented and introduced in [181] based on the data-driven object-oriented declarative modelling language Modelica. Then, these data are fed into a decision tree-based algorithm to diagnose faulty situations in satellites.

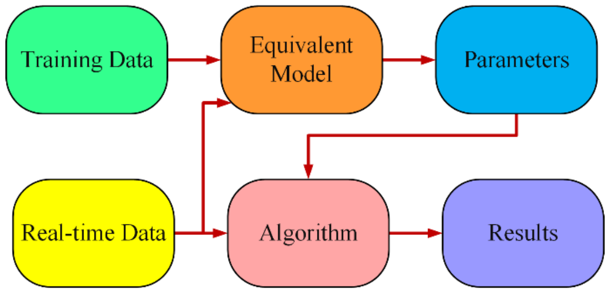

FIGURE 17. SOC and SOH management algorithm.

IV. THE CHALLENGES OF USING DIGITAL TWINS IN CONDITION MONITORING OF THE AVIATION INDUSTRY

A. SENSOR'S PROPER FUNCTION

Sensors are the link between the real system and the virtual domain that receive the data from the real domain and send them to the virtual model. Failures and errors in sensors may not be tolerated since any failure in sensors results in wrong information about aircraft, consequently a wrong decision, and thus, a catastrophic crash. So, to avoid these consequences and outcomes of sensor errors, there are some challenges that must be recognized and then addressed. The very first challenge is corruption and loss of data due to the imperfect operation of sensors, wirings, and receivers [182]. The loss or corrupted data results in wrong decision-making about the operation condition of aircraft, making false protective actions, etc. To avoid data loss, many methods have been proposed in literature such as K-nearest neighbours [183], Delaunay triangulation [184], multichannel singular spectrum analysis [185], and compressive sensing [186]. By applying these methods, the value of loss/corrupted data could be estimated and as a result, the possibility of wrong decisions is minimized. Another challenge of sensors is related to the accuracy that they offer for measuring a specific quantity. Consider a sensor that is used to measure the temperature inside the engine and send it to the virtual domain for protective issues. Assume that the real value of temperature is about 400.556 Fahrenheit and the threshold value for some protective actions is designed to be about 400.55. Under such circumstances, there is a need for a sensor unit that is capable of measuring temperature in up to three decimal places to avoid any failures in aircraft engines. The required accuracy up two to three decimal places necessities using some specific type of sensor with a specific operation condition, and a higher purchasing cost in comparison to the same sensor with a measurement capability of just two decimal places. Another challenge is the performance of sensors under harsh operational conditions such as extremely high temperatures for sensors inside the combustion engines, the high pressure and cold environment for sensors on the body of aircraft and outside of the cabin, etc. Under such harsh conditions, the appropriate performance of sensors might be decreased, and the measured value have a large amount of inaccuracy to avoid this, a specific range of sensors for such conditions is required that could operate with high performance and reliability without loss of accuracy. Finally, there is a calibration process for sensors that could take less than hours to more than tens of days. Calibration refers to a series of processes that adjust the sensors so that they illustrate and receive data error-free and with the highest possible accuracy. Numerous methods and procedures are defined for making sensors calibrated which are discussed in [187].

B. DATA SCIENCE AND DATA PROTECTION

data science is the common point of three fields of science, namely computer science, mathematical science, and business knowledge. The most important task of a data scientist is extracting useful information from received data by sensors and deciding, strategic planning, etc. [188]. By digitalization of aircraft control, design, management, maintenance, overhaul, etc. through DTs, data science and data scientists are gaining a high-valued position. In aviation units, especially in the CM of aircraft and due to the sensitivity CM process, data scientists must be capable of making the most appropriate choices without any risk of aircraft failure or crash. The first challenge that they must face is the problem of the large amount of data that is received and must be handled, known as big data. Usually, big data is defined based on 4V parameters which are Volume, Velocity, Variety, and Veracity, volume concerned with the fact that data is generated constantly and without any pause while velocity refers to the fast nature of data generation, especially for DT applications. Variety is related to the fact that data are generated by multiple sources and in different types such as voltage signals, health conditions, etc. and veracity concerns about the quality of data received by DT [189], [190]. The other challenge that data scientists must face is related to the security and protection of data. Data security must protect the databases against cyber-attackers, ransomware is a kind of malware designed to deteriorate data, and data theft [191]. Data security becomes even more sensitive when DTs are used for condition monitoring of aircraft and any kind of data theft, cyber-attacks, and malware could jeopardize the safe operation of aircraft and threaten the lives of passengers [192].

Overfitting of AI-based methods is a statistical phenomenon that takes place when a function with the same inputs results in a different output. This reduces the accuracy of the training, testing, and validating process and causes a high value of error between real data and the estimated one [193]. As mentioned before, due to the nature of DTs for aircraft and imperfections in sensor functionality, overfitting is highly possible in virtual domain, especially if they are modelled by AI-based techniques. Overlearning is another phenomenon that originated in imposing large amounts of data into a machine learning-based model and because of this model may present some inaccurate and non-reliable results that cause the system operator to make wrong decisions.

C. REAL-TIME DECISION-MAKING AND COMPUTING

During the application of DT-based solutions to industrial manufacturing processes, the need for control and compliance with Quality of Service (QoS) specifications, e.g., in terms of maximum allowed latency or minimum reliability, was widely recognized [196]. This is of central and crucial relevance also in the case of DT for aircraft condition and fleet monitoring situations, where a fundamental requirement must be granted at execution time. This is to guarantee an upper bound on the maximum latency allowed for the operation series: in-the-field

IoT data collection, IoT data filtering/aggregation/transfer to the digital twin, digital twin data processing and decision making, generation of a consequent control/reconfiguration command, and received of the command at the in-the-field associated actuators (full control loop).

The technical challenges related to guaranteeing QoS for real-time decision-making and IoT data processing of DT are exacerbated by the fact that DT almost always runs on virtualized computation, storage, and networking resources that are due to the widely recognized scalability and economic motivations. For instance, in the EU H2020 IoTwins project, guaranteeing the latency for communication and also the processing of industrial IoT data for automation control by industrial DT were widely investigated [197]: controlling and managing latency over virtual networks and distributed Docker containers require advanced orchestration capabilities and a holistic view of network quality management, message queue prioritization, and microservice invocation (e.g., Function as a Service invocation in a serverless execution environment [198]); novel middleware should consider, in a synergic way, network acceleration techniques (e.g., RDMA, DPDK, XDP, and TSN-compliance whenever available in the deployment environment), edge cloud computing opportunities (see Section IV-E), message-oriented protocols with high-efficiency prioritized queues, and differentiated invocation mechanisms for local processing functions (e.g., based on dynamic library loading, WASM, or the more traditional posix_spawn API) [196].

Some recent research work in literature has started to explore the technical challenges. So far, this was mainly conducted by considering the opportunistic usage of edge cloud resources to improve latency and jitter [199], [200]; these potential advantages in terms of latency and jitter started to be recognized as the key factor for wide adoption of the edge cloud computing programming paradigm [201]. Although the coordination and coupling of different prioritization mechanisms is not a recent issue, with the recent advent of next-generation networking, it has gained an increased research interest. The need for concatenation of mechanisms has been considered as a primary problem that is presented at different levels of the stack to build a complete feedback control loop, e.g., when applied to industrial automation, since the earliest distributed systems. To tackle the issues of resource orchestration and partitioning while guaranteeing QoS levels at the edge, reference [202] proposed DRAGON: this reference describes some implementation insights about DRAGON and evaluates its performance compared with traditional orchestration approaches. The introduction of middleware for the concatenation of QoS-aware mechanisms is a frequent design pattern applied in the literature to reduce complexity [203]. In [204], the authors proposed a technique to couple priority and reservation based QoS management mechanisms, at the operating system and network layers, through distributed object computing middleware. In [205], the authors presented a middleware built on CORBA to provide distributed soft real-time applications with a uniform Application Programming Interface (API) to reserve heterogeneous resources with real-time scheduling capabilities in a distributed environment. This solution introduced uniform interfaces to support the reservation of CPU, disk, and network bandwidth on Linux systems. Even if Serverless computing and Function-as-a-service (FaaS) platforms are relatively novel, some platform improvements have already been proposed in the literature to achieve better FaaS performance and in particular latency reduction [206], [207], [208]. Some papers have proposed the deployment of serverless platforms on edge nodes to achieve better QoS [206]. The usage of different invocation methods to speed up function startup has been proposed as the exploitation of cross-compiling to achieve faster executables. For example, in [207], the authors proposed Faaslets, an isolation abstraction that exploits WebAssembly to achieve good isolation and fast function startup; they have also proposed an additional optimization with a mechanism to restore from already initialized snapshots that resulted in platform improvement throughput and tail latency. In the proposed project Catalyser [208], the authors presented a serverless sandbox system to enhance function startup and isolation. To provide a fast startup, Catalyser exploits a checkpoint mechanism to skip initialization and a new OS primitive to reuse the state of the running sandbox; this results in a relevant reduction of the startup time of function invocations (i.e., less than 1 millisecond in the best cases).

D. MODELING ISSUES

Modelling is the beating heart of the DTs in aircraft units that reflects the exact characteristics of the aircraft or its components in a virtual domain. Modelling could be performed based on three methods, White Box Model (WBM), Grey Box Model (GBM), and Black Box Model (BBM). This section is dedicated to the challenges and advantages of each one of these modelling methods. WBMs also known as conventional models are a type of modelling that characterize the behaviour of aircraft, engine, wings, etc. by means of well-known and accepted methods such as FEM, Equivalent Electrical and Thermal Circuit (EETC), Finite Difference Method (FDM), Volume Element Method (VDM), etc. WBMs are usually accurate and reliable while their computation speed is much lower than other types of modelling. However, with advancements in distributed computation and edge computation, their speed could be further increased [209]. Figure 18 shows the commonly used software packages used for aircraft modelling.

Unlike WBM, in BBMs, outputs are estimated based on a previously acquired knowledge of data without any physical interpretable nature. BBMs are usually ultra-fast, adaptive, and re-trainable against new situations while their most significant disadvantage is their highly dependence nature on data. This means that any data corruption, bad data, lack of data, etc. could result in inaccuracy and falsely made decisions [210]. GBM has been proposed to overcome both issues of WBM and BBMs that take advantage of both models to correlate between inputs and outputs. This means that both physical logic and data science are used to characterize the behaviour of understudied components. These kinds of models are the most appropriate types of models for being used in DTs due to their high accuracy, adaptability, fast estimation nature, reliable results, etc.

E. THE 5G SUPPORT FOR DIGITAL TWINS IN THE CLOUD CONTINUUM

To minimize latency and improve data locality, there is an emerging trend in designing, implementing, and deploying distributed DT, capable of running in the so-called cloud continuum [197]. In this context, the cloud continuum is the set of distributed nodes, spanning from data centre cloud nodes and ETSI Multi-access Edge Computing (MEC) nodes in the 5G infrastructure to industrial gateways, fog networking routers, and even IoT devices. Usually, DT may be distributed so that they can run a first training phase for determining their data-driven model at traditional data centre nodes; once the model is trained, DT can run even on either industrial gateways or MEC nodes to access IoT-generated data more locally and efficiently, possibly by generating control and reconfiguration commands in the proximity of their actuators; in addition, distributed DT on industrial gateways or MEC nodes can continue the training/learning process also locally, via emerging machine learning techniques such as refinement learning [211] and federated learning [212].

In the perspective of running DT in the cloud continuum, the role played by wireless technologies is essential with i) extremely low latency and ii) local edge computing facilities.

On the one hand, 5G and Beyond 5G (B5G) networking offers a significant evolutionary step in terms of Ultra-Reliable and Low-Latency Communication (URLLC) with even the possibility to specify, to some extent, guarantee predictable performance [213]. In fact, 5G and B5G specifications include the requirement for the network infrastructure to expose its performance toward an end-to-end orchestrator so that the end-to-end service can be configured; accordingly, this end-to-end orchestration is the same sketched above and envisioned by DT in the cloud continuum for holistic resource management. To develop 5G and B5G radio network solutions, the industry and standardization are pursuing two technology tracks that are ongoing in parallel. One builds on an evolution of the 4G Long-Term Evolution (LTE) radio interface and the other builds on a New Radio (NR) interface. Long-Term Evolution (LTE) has been standardized in 3GPP Release 8 in 2008 and has been enhanced in every new standard release. Starting from Release 15, LTE introduces URLLC and addresses the corresponding 5G requirements. The LTE evolution can be introduced into existing LTE

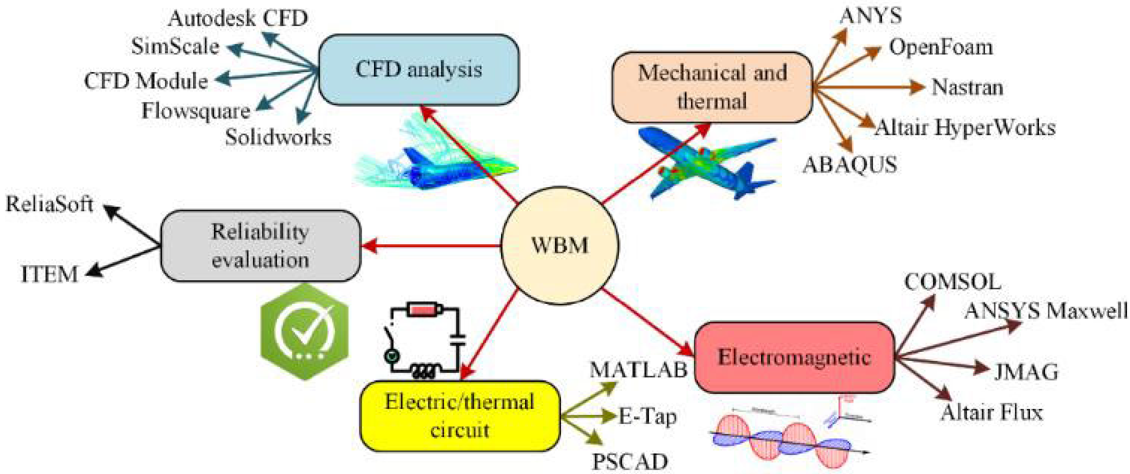

FIGURE 18. The different software used for different purposes in aircraft systems, adapted from [194], [195].

networks and spectrum allocations: it provides 5G functionality in a backwards-compatible way, which means that new LTE-evolved devices can make use of novel 5G features, while old LTE devices can continue to operate within the same LTE system with the legacy capabilities. NR, in contrast, is not restricted by backward compatibility, and can address design opportunities for a lean design. For latency minimization, the primary radio design choices and innovations that were included in the 5G standard specifications relate to waveform optimization, improved resource access strategies/mechanisms, and optimized channel access. Additional details about the related mechanisms and protocols may be found in [213]. Note that, with those improvements, the guaranteed upper bound for the radio access network latency that can be achieved in 5G varies from 0.25ms to 3.2ms depending on the employed URLLC configuration.

On the other hand, the European Telecommunications Standards Institute (ETSI) MEC specification provides a fundamental contribution to the open and standard realization of the cloud continuum concept, by offering a virtualization platform and architecture integrated into the 5G/B5G network infrastructure, thus representing an essential element for current and future distributed DT. In fact, according to ETSI, MEC offers "IT service environment and cloud-computing capabilities at the edge of the mobile network, within the Radio Access Network (RAN) and near mobile subscribers" [214]. Examples of MEC applications include caching of contents to deliver to customers, tracking of devices, and hosting of decentralized DT for motion control and industrial automation. According to ETSI [215], the general entities involved in the MEC architecture are structured based on three levels: the upper one is the MEC system level, which has a global visibility on the MEC architecture and therefore coordinates every block in the levels below. In the middle, the MEC host level includes MEC host and MEC host level management. The MEC host is an entity that includes the platform and the virtualization infrastructure used to run the MEC and provides network, processing, and storing virtualized resources dedicated to MEC-hosted applications such as DT. MEC services are provided and consumed by MEC applications or the MEC platform itself. Some examples are the Radio Network Information (RNI), which gives information on the radio network state, the location service, which gives location-related information, and the bandwidth manager service, which helps in prioritize and handle traffic. Containers or virtual machines run as well in the MEC host: typically distributed digital twins run on containers, e.g., to locally execute anomaly detection based on machine learning models initially trained on the cloud. At the bottom of the stack, various transmission entities such as the 5G infrastructure and local/external networks may be present according to the ETSI architecture.

F. THE SENSITIVITY OF CM IN AIRCRAFT

Except for CM, as mentioned before DTs could be used in the pre-design, design, manufacturing, maintenance, and overhaul stages of an aircraft. In these stages, any failure in DT could result in malfunctions in the structure of the aircraft before the flight mission that could be diagnosed while this is not the case for DTs that are used during flight missions and for CM purposes. Any failure or error in the virtual domain, decision-making process, sensors, wirings, etc. results in malfunctions of aircraft during a flight mission and this could result in explosions, crashes, and many other tragedies. This is the most challenging issue for using DTs as the main component in decision-making, condition monitoring, protecting, and controlling of aircraft. Thus, for such a sensitive goal, the DT model must be error-free and with the highest possible accuracy while it must be also real-time. The real-time nature of DTs is the most important characteristic of the virtual domain that enables an ultra-fast response to any kind of changes, failures, faults, etc. during a flight mission so that it protects aircraft against any possible damages, crashes, and component failure.

V. FUTURE TRENDS

A. FUTURE TRENDS FOR ELECTRIC AIRCRAFT

During the last few years, the rate of daily flight missions has increased significantly initiating an extensive increase in fossil fuel combustion. Thus, a large amount of greenhouse gases was released into the Earth's atmosphere, and this has intensified global warming and emissions. To overcome this issue along with the challenge of shortage of fossil fuels, scientists have proposed restructuring the aircraft systems [216], [217]. One of the proposed structures is the electrification of aircraft drivetrain by using electrical devices. Under such circumstances, to reduce the power loss and voltage drop, the generated power is converted to DC voltage by using power electronic devices and then electrical energy is delivered to electrical motors, operating as the main part of propellers. In this region, DC power is again converted into AC by means of power electronic devices [218]. The expressed structure was the structure of a hybrid electric aircraft while there is also another type of aircraft, known as full electric aircraft in which batteries and fuel cells replace the electrical generators and directly feed the electrical energy to propellers [219]. There have been many successful prototypes manufactured for electric aircraft that are discussed in detail in [219] while the most successful and most researched is NASA N3-X turboelectric distributed aircraft [220], [221]. Although electric aircraft offer a wide range of solutions to challenges of emission and pollution, the power density of conventional power devices is still lower than expected. Thus, superconductors have been proposed as cryogenic counterparts of conventional power devices with a much higher power density, 5x to 10x higher than conventional power devices [222], [223]. However, the need for the cryogenic environment for proper and safe operation of cryo-electrified aircraft [224] has put doubts on using superconductors in aircraft drivetrain. This is because cooling systems usually have a high specific mass, low reliability, and high purchasing costs [225]. To resolve this issue, another concept has been also added to the re-structuring process of aircraft, known as cryogenic fuel aircraft, where combustion engines operate with fuel like Liquid Hydrogen (LH_2) [227]. As reported in [228] and [229], LH_2 is used as a cryogenic coolant fluid for superconducting devices and cryogenic power converters and after that the LH_2 is warmed up or vaporized during heat loads, it is injected in combustion engines as fuel, or it is stored in fuel cells. This type of aircraft presents high-power density for electrical systems, a low specific mass for cryogenic systems, and low emission and pollution for aircraft as shown in Figure 19.

B. FUTURE TRENDS IN DT

Among the several envisioned trends for the DT of the future, for condition and fleet monitoring, three primary lines of evolution are identified.

Firstly, digital twins are going to have more and more "twins" in a strict sense and not only digital models or digital shadows. According to precise technical definitions, a digital model is just a digital representation of a physical system, not exchanging data flows with the real world (e.g., the physical model of a wing or the electrical model of a circuit). On the contrary, a digital shadow is a digital representation of a physical system capable of receiving data flows from the real world to refine, either statically or dynamically, its model in the cyber world (e.g., digital shadows can exploit IoT data flows from sensors and machine learning to define/refine their models). Digital twins are more than digital shadows in the sense that they can interact with the real world via bidirectional data flows, not only to refine data-driven models with IoT data at runtime but also to command actuation feedback by possibly intervening on the conditions of the physical world (e.g., reconfiguration of a production line in prescriptive maintenance or modification of fleet paths).

The second relevant trend to highlight is the evolution of distributed digital twins towards being hybrid, i.e., employing synergically their double nature of both model-driven (exploiting mathematical/physical models of the physical object counterpart) and data-driven (exploiting machine learning-oriented models, fed by IoT data initially or during full-service provisioning). Only with this double nature of model-driven plus data-driven, future hybrid digital twins will be able to achieve the level of precision and accuracy that are needed in several critical vertical domains, such as aircraft condition and fleet monitoring. Note that hybrid digital twins may exploit iterative cycles to refine their combined model-driven plus data-driven representations of physical counterparts, thus producing successive generations of digital twins evolving towards always better precision.

Finally, the third envisioned trend is towards being more and more distributed, thus taking full advantage of all the opportunities made available by the cloud continuum concept. Distributed execution on edge nodes, as already mentioned, will be central for more efficient control of QoS parameters and better compliance with privacy/security requirements via localized exploitation of local IoT data. This stress on distributed execution will benefit and leverage, in turn, the emergent trend towards innovative distributed techniques for machine learning, such as federated learning.

In future, DT would be more efficient and more reliable through the improvements of the machine learning and deep learning methods. One of the future advancements of the AI-based techniques is Explainable AI (XAI). In this context, XAI is defined as the series of actions that make the decision making by AI techniques. This would build trust in community while ensuring the accountability. To develop XAI, there are two important phases. The first phase is related to understanding the model where stakeholders cross check the model during training. This is done to make sure that accuracy of the model is as high as expected. Understanding usually consists of debugging, bias detection, scientific understanding, robust model creation, and auto model cre-

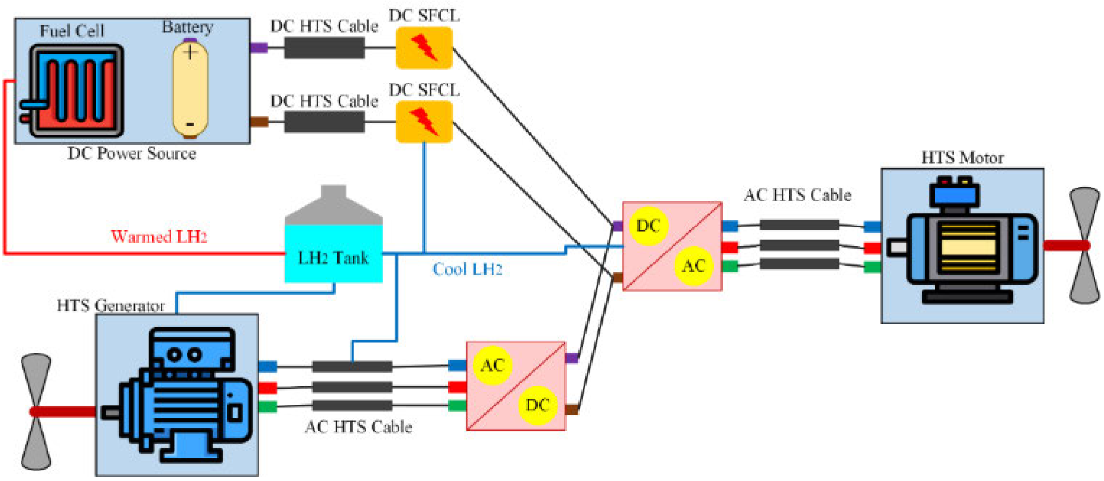

FIGURE 19. The overall structure of hydrogen-superconductor-based aircraft, adapted from [226].

ation. Second phase is explaining phase where AI model is developed and implemented for real-time application. Here, the decision-making process would be clarified for the end users trying to explain them how the decision is made [230]. Another upcoming trend for AI-based techniques is Generative AI (GAI). which is defined as systems that take the advantage of deep learning methods for contents like human generation where these contents should be a response by humans/machines, where ChatGPT is the best example of GAI [231].

DTs are currently implemented in part of the complex systems or just a system without any consideration of other dependent systems. In future, DTs should be used for very complicated systems or for the whole procedure. For this purpose, they should have scalability, interoperability, expansibility, and fidelity. In this context, scalable DTs are those that based on the research object, the data and the contents are changed. Interoperability is referred to the interaction capability of different models in DT that are used for same/different purposes, such as maintenance or monitoring. The reconfiguration capability of DTs regarding the structural, physical, etc, changes in main system is also defined as expansibility. For the sake of creating an DT for a complex system, firstly system should be divided to multiple subsystems. Then, subsystems should be divided to different tasks, models, requirements, factors, etc. After that, information fusion happens, where all information gathered from different sources and subsystems. Then, associations are scaled, and context coupling happens, Finally, a complex digital twin would be created [232].

Another upcoming trend for DTs is the concept of Virtual Manufacturing. This is referred to the use of computer-based models and simulations for design, test, and manufacture of the products, without they manufactured physically. Indeed, VM leverages on technologies like AI, IoT, and big data analysis. VM reduces the manufacturing costs for all companies that participate in manufacturing a device, this includes design, test, and manufacturing companies. VM also increases the efficiency of the products and the manufacturing lines. This is done by reducing the amount of waste, increasing the productivity, etc. Another positive fact about VM is that they reduce the ''time to market'' index for products. It means that by using VM, companies can start to sale their products in marker, sooner, compared to physical manufacturing processes. This would also increase the quality and safety of the product s by monitoring the manufacturing lines, controlling the anomalies that happen during the manufacturing, etc [233].

Augmented Reality (AR) is accounted as a technology that use digital information of a real world to improve the user's perception of the world. AR can be used for navigation applications where the related apps could show the virtual directions to the user to guide her/him to the destination. It can be also used for training and education purposes in sensitive applications like surgery on human body [234]. Then, there is Virtual Reality (VR) where it is defined as the re-creation of the current real world through digital items like images, videos, models, etc. In this manner, instead of observing the consequences of some act, one can experience it in digital world. Generally, there are three types of VR, non-immersive VR, immersive VR, and semi-immersive VR. Finally, there is Mixed Reality (MR) where the real-world scenarios are superimposed to the digital elements of the models through a real-time connection. This would allow the real-time connection between physical and digital connection in DTs, in a real-time manner [235].

The recent advancements on IoT and DT have emerged the existence of a new concept as ''Edge Computing (EC)''. Since the number of that must be analysed, in IoT and DT, is too much. EC is accounted as one of the most important future trends for DT and IoT technologies. The idea behind EC is to do all data processing, computations, and storage of data to the edge of networks, instead of clouds. As a result of this, data transmission time and response time are reduced as well as the reduction of the pressure on the shoulders of the bandwidth [236].

C. FUTURE OF DT IN ELECTRIC AIRCRAFT

One of the future trends related to the using of DTs for electric and cryo-electric aircraft is performance prediction of the electric devices. For this purpose, AI-based DTs will be used to replace the FEM-based methods. The DTs, in this regard, could be used for condition monitoring of electrical devices, anomaly prediction, fault location, etc. Another future application of DT in electric aircraft is controlling the power electronic devices to ensure their safety of operation. To do this, the cooperation of the power electronics and AI-based techniques could not only control the power electronic device but also could be used to monitor its temperature, anomalies, etc. DT would be used also for decision making tasks to control and guide the electric aircraft. Also, the decision-making responsibilities related to energy source management in electric aircraft would be handled by DTs.

Health monitoring of passengers during a flight is another future trend for DTs in aviation units. This is accessible by using the biometric sensors that could be implemented in aircraft seats or cabin surfaces. Then, in a real-time manner, data of these sensors are collected and processed through AI-based techniques. After data analysis, the health profile of the passenger would be acquired. In any case that passenger's health profile become anormal, the In-Flight Services would help the passengers, DT would be also used for training and testing the pilots where this can reduce the chance of crashes and human errors. For this purpose, DT could be used scenario-based flight simulations, where a wide range of realistic scenarios are created to help the training procedure of pilots. It can be also used to familiarize the pilots with the cockpit.

VI. CONCLUSION

Exact and fast monitoring of the aircraft units could reduce the risk of jeopardizing the passengers' lives and decrease serious economic damages to aviation fleets. Recently, a novel concept has been applied to the monitoring process of aircraft units, known as Digital Twins (DT) which is a virtual domain that is simulated exactly as the real twin works. 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. Then, in section two of the paper, the DT concept is completely established and defined. Afterwards, in section III, 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. In the second stage of section III, the lessons learned for DT technology from other industries have been reviewed and how these lessons could help us in the aviation industry. Section IV was dedicated to the current challenges of both aircraft and DT systems and lately, section V was presented to show the future trends in the DT field and aviation industry. The most important highlights of this review paper could be shortlisted as follows:

- Among the published papers, approximately 10 papers have used the conventional modelling methods for DT.
- Artificial intelligence techniques have been used in 12 papers for condition monitoring purposes of DT.
- The DT-based condition monitoring methods, reviewed in this paper, are mostly dedicated to fault/failure diagnosis in the body of the aircraft or for controlling the aircraft.
- Crack detection and Life prediction on wings are of the most discussed topics, regarding using DT for condition monitoring.
- Marine, power systems, and space programs also have used the DT for condition monitoring purposes.
- Sensors, real-time decision-making, data safety, and 5G support seem to be current obstacles for using DT in condition monitoring of aircraft.

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 cryo-electrification 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.

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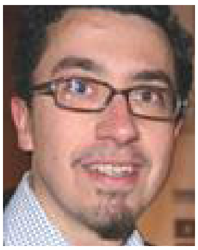

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