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Review article

Digital twins for aircraft maintenance and operation: A systematic literature review and an IoT-enabled modular architecture

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ABSTRACT

Thanks to the rapid growth of the Industry 4.0 domain and the innovations brought by the Internet of Things paradigm, Digital Twins (DT) are increasingly gaining momentum in our society and various companies are moving towards their adoption in many application areas. One of them is the aerospace sector which has started to take advantage of their innovative services to enhance workers' daily duties. Although different works already proposed solutions to apply the Digital Twin to the industrial domain, the airspace area has not yet completely benefited from its advantages. Digital Twins carve out an important role in the entire aircraft lifecycle management, in particular they provide value in the maintenance process by gathering status information for optimizing aircraft operations. This article aims to comprehensively analyse, by applying the systematic mapping method, the current state of the art on Digital Twin technology applied to aircraft operation and maintenance. The results give an overview about the innovations that the Digital Twins can bring in the specific current state of the art, by highlighting the modelling approach used for building the DT, and the most important extracted common information related to the most frequently adopted tools and the covered subsystems. As a further important contribution to the research community, this work provides a comprehensive modular architecture that acts as a summarizing artifact able to serve all the analysed works and discusses the open issues by pointing out some interesting research directions, that could lead to new and interesting future works and collaborations.

1. Introduction

The Digital Twin (DT) concept emerged many years ago in 1991 when it was mentioned for the first time in the publication of David Gelernter [1] and was taken up some years later by Professor Michael Grieves in 2002 during his university course. The term was introduced by NASA in their proposals for space roadmaps and exploration [2,3]. The most commonly used definition of Digital Twins declares them as virtual representations of a physical asset, whose condition is reflected through historical or real-time data captured by sensors [4,5]. Such a definition highlights how it is an extension of the Internet of Things (IoT) domain that actually groups all the technologies, techniques, and sensors with the aim of sharing information and services among objects called "things" [6,7]. In fact, as declared by [8] digital twins take real-time IoT data and apply AI and data analytics to optimize performance, provide features, expose services, etc.

With the advent of Industry 4.0 and the advances made in Big Data analytics and Machine and Deep Learning (ML/DL), the Digital Twin has been spreading to several industrial fields, and in 2019 75% of industrial world organizations were planning to use

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its innovative technologies in their business processes [9]. Nowadays, the DT continues to show an increasing trend and its market adoption is expected to grow heavily in several years [10]: it is estimated that by 2027 almost all the IoT platforms will contain digital twinning capabilities [11].

In this work, particular emphasis is placed on the DT for Integrated Vehicle Health Management (IVHM) [12] in the aerospace field. IVHM, also known as Integrated System Health Management (ISHM), is used to group all the systems that have the capability of assessing the current or future health state by carrying out diagnostics and prognostics procedures after condition monitoring. Digital Twins play an important role in IVHM systems by validating detections, guaranteeing reliability, and acting as an alternative representation of the aircraft platform, as stated by Ezhilarasu et al. [13]. Diagnostics relies on the process of collecting, fusing, and analysing data to determine and isolate possible causes for fault modes. Prognostics tasks, instead, involve future health status prediction, by monitoring and evaluating the current one. Prognostics aims to determine the Remaining Useful Life (RUL) [14] of a component by giving its state of wear and, eventually, the environmental conditions [15]. IVHM systems follow the Open System Architecture - Condition Based Maintenance (OSA-CBM) [16] framework, which defines the guidelines for such kinds of systems: it defines a set of essential building blocks and their interactions in a condition-based maintenance system. A specific related research area is predictive maintenance, in which it is possible to maximize the life of an asset by scheduling work in advance based on a life estimation calculated on monitored parameters, history, and constituting materials.

Various reviews can be found in the literature aimed at analysing the existing solutions for Digital Twin proposals. Nevertheless, within the present paper, we focus on reviewing the literature to identify all the existing works focused on the Maintenance, Repair, and Overhaul (MRO) systems [17] applied to the aviation industry. We applied the systematic mapping process to analyse solutions published between 2018 and 2023, highlight the main characteristics of the analysed papers, and propose an IoT-enabled modular architecture that could serve all the analysed works and inspire future development directions.

The rest of the paper is organized as follows. Section 2 discusses the main related works. Section 3 describes the adopted research methodology and the research questions that guided our work. Section 4 presents the results obtained by applying the research methodology. In Section 5 the answers to the research questions guide the definition of a comprehensive IoT-enabled modular architecture that resumes the key concepts and potential open issues that can motivate future works. Finally, Section 6 draws the conclusions.

2. Related work

As already mentioned in the introduction, within the present paper, we systematically analysed existing works focused on the Digital Twin technology applied to the aircraft sector, and therefore on the Maintenance, Repair, and Overhaul (MRO) systems applied to the aviation industry. To the best of our knowledge, no other reviews already performed such a similar specific investigation, however, it is worth mentioning the works that already provided general information or discussions on the topic.

First, it is important to mention the paper presented by Luning et al. [18], which is the first work that introduces the role of DT in the aerospace field. It surveyed the main concepts and technologies behind Digital Twins by highlighting their potential value as enablers for the aerospace domain. The main outcome of the paper regards the data and its management, in fact, the authors reported the main challenges in optimizing massive data management (in terms of transferability, processing and analysis) to build high-fidelity aero-DTs for different vital aircraft systems.

Aydemir et al. [19], instead, contributed in listing the available approaches and technologies, in addition to the challenges facing Digital Twin and the future of Digital Twin for aircraft.

Van Dinter et al. [20] presented a systematic literature review (SLR) aimed at identifying the features, challenges, and research directions of predictive maintenance using Digital Twins. Although it is not focused on the aerospace sector, the authors extracted and highlighted general information that is valid for all the application domains they identified in the review. Their work looks at the benefits of Digital Twins as a predictive maintenance accelerator and highlights the lack of flexibility of industrial Digital Twin platforms. However, among the other outcomes, they provide heat maps for approaches that could enable researchers to comfortably find the key approaches and algorithms to use when developing a predictive maintenance module for each Digital Twin representation type also in the aerospace domain.

D'Amico et al. [21] presented another thematic review and characterized DTs in terms of technology used, applications, and limitations in the context of maintenance and degradation. Although, also in this case, the review is not focused on the aerospace domain it reports information that is also valid in this field of interest. In fact, they mainly answer general research questions such as: (a) How DTs for the maintenance phase of the life cycle are developed?, and (b) How can a DT be characterized for maintenance?. Therefore, they mainly discuss how the aerospace sector could benefit from the application of DTs and highlight the main issues that usually affect maintenance activities that could be solved or improved by DTs.

Another interesting work is the one proposed by Qian et al. [22] where the architectures of DTs, data representation, and communication protocols are reviewed to then highlight existing efforts on applying DT into IoT-based data-driven smart systems. They mainly focused their attention on various application domains such as smart grid, smart transportation, smart manufacturing, and smart cities. Therefore, also in this case, the aerospace domain was not considered, however, the authors summarized concepts and ideas that are also valid in such a domain: some challenges still exist from Cyber–Physical Systems (CPS), data science, optimization, and security and privacy perspectives. In addition, the possible future research directions mentioned by the authors have been taken into consideration in defining the ones reported in our paper.

Digital Twins are also mentioned in some reviews on the possible application of IoT in various domains. For instance, Dias et al. [23] highlighted how IoT reference architectures (e.g., IoT Architecture Reference Model (ARM) based on IoT-A) can be used to represent basic functional components from an information viewpoint and emphasize that their core parts are virtual entities (i.e., digital twins). In addition, although the work proposed by Hayward et al. [24] is focused on Indoor Location Technologies, it discusses how Cyber–physical systems utilize multi-directional links between physical phenomena in the real world and appropriate cyber representations of those phenomena through the capture and processing of data from smart devices and the Industrial Internet of Things, thus exploiting DTs models. Another recent work presented by Wang et al. [25] discusses a preliminary review that investigates and evaluates the quality and stability of appropriate DT techniques in real-world aircraft Maintenance, Repair, and overhaul (MRO) activities. The authors identify two main categories of DT models applied to the MRO sector, i.e., Data-Driven and Model-Based models, and evaluate the applicability of the two models to vehicle system management. In addition, the work presents a methodological approach for Predictive Maintenance development and proposes a framework for electrical actuation health management and prognostics. The results provide a preliminary analysis of the sector by identifying some key points and useful information that has been exploited within the present work, that, instead, systematically more generically analysed the literature and propose a comprehensive architecture to serve all the analysed artefacts.

Finally, some other related works present general information on the application of DTs and propose future works and challenges that are valid for the aerospace domain: the works presented by Da Cruz et al. [26], Gill et al. [27], Rathore et al. [8], and Thelen et al. [28] can be grouped in such a general category and have been used to confirm strong scientific motivations of the present work.

The exposed analysis demonstrates on one side the interest of the research community in the IoT-enabled infrastructures specifically known as Maintenance, Repair, and Overhaul (MRO) systems, while on the other side highlights the absence, and therefore the need, of a comprehensive literature review that specifically identifies and analyse all the existing works focused on the MRO systems applied to the aviation industry. To this aim, the present paper comprehensively analyses, by applying the systematic mapping method, the current state of the art, giving an overview of how the Digital Twins, seen as an IoT evolution, can contribute to enhancing the MRO sector applied to the aviation industry. The results highlight the modelling approach usually used for building the DT and summarize the most important common information related to the most frequently adopted tools and the covered subsystems. As a further contribution to the research community, this work provides a comprehensive modular architecture that acts as a summarizing artefact able to serve both all the analysed works and other future works to be developed within the domain. Furthermore, this paper discusses the open issues mainly encountered in the analysed works by reporting some interesting research directions, that could lead to new and interesting future works.

3. Research methodology

This study follows the systematic mapping approach [29] to summarize the contributions that exploit DT technologies, a combination of IoT and other innovative solutions (e.g., AI and data analytics) to aircraft systems. This review has two primary purposes: to support all the researchers interested in the domain by providing an overview of the latest innovative techniques in building DT solutions in the aircraft maintenance field and to capture in a single IoT-enabled architecture the recurrent practices and possible future works to face main open challenges.

The steps followed in the research process consist of: (1) identification of the research questions, (2) definition of a representative query to search papers on citation databases, (3) removal of unhelpful articles, (4) extraction of new keywords from the solutions identified in the previous steps, (5) data extraction and analysis of the papers.

The research questions that guided this review are reported in the following list:

- RQ1 Is there a preferred approach and which software tools are used for building Digital Twins in the field of maintenance, due to failures in the aircraft components?
- RQ2 What safety-critical components of an aircraft prone to failures are covered and which kind of approach is preferred for each topic?
- RQ3 What type of knowledge can be extracted to design a data-driven modular architecture?
- RQ4 What are the open issues to be further investigated?

As a first action, the key terms of interest were singled out to combine them into a single search query, shown in Listing 1, for conducting research into "Title", "Keywords" and "Abstract" on the most spread search engines for Scientific domains [30]: Scopus (www.scopus.com), IEEExplore (ieeexplore.ieee.org) and ACM Digital Library (dl.acm.org).

Listing 1: Search Query

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("digital twin" OR "virtual twin" OR "virtual model" OR "virtual replica" OR "virtual representation" OR "
    digital surrogate") AND ("data—driven" OR "sensor failure" OR "condition monitoring" OR "condition
    based maintenance" OR "remaining useful life" OR "rul" OR "predictive maintenance" OR "fault detection"
     OR "fault diagnosis" OR "fault tolerance" OR "performance monitoring" OR "performance degradation" OR
    "anomaly detection" OR "ivhm" OR "ishm" OR "health management" OR "health monitoring" OR "osa—cbm")
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Due to the technological progress in several related fields which provided the upward trend of the DT concept in the last years, only journals, reviews, and conference papers from January 2018 to July 2023 were taken into consideration. The merging of the key concepts refers to many general areas of interest, therefore as an inclusion criterion, only solutions strictly related to the application of IoT and AI to aircraft were considered. Indeed, to mention the most common type of innovation brought into the

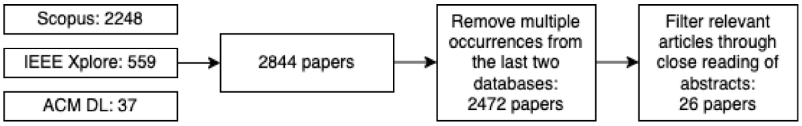

Fig. 1. The entire selection process.

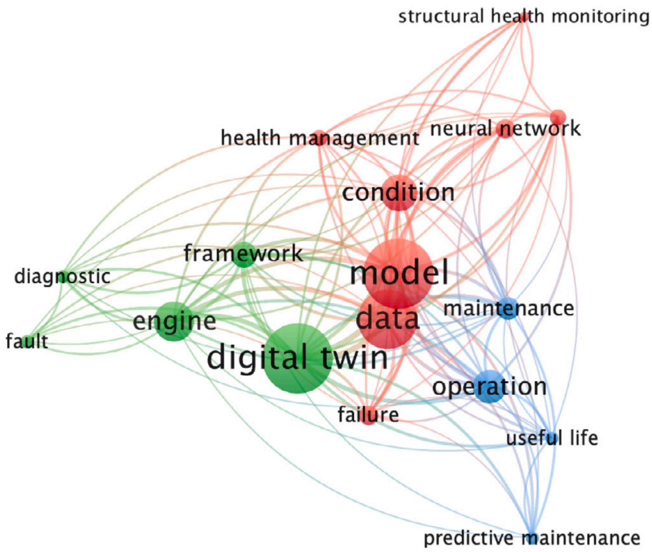

Fig. 2. Co-occurrence map based on the most relevant terms within the abstracts with binary counting.
Source: Created with: [31].

field, we excluded all the articles focused on innovations in computer vision, augmented and virtual reality domains. In addition, we decided as an additional exclusion criterion, to rule out all the duplicates, incomplete publications, non-English papers, and the ones that were not accessible (e.g., due to authors' established policy). Afterwards, the resulting final list of relevant papers was used to extract further main keywords through the VOSviewer tool [31] and in the last step, the identified studies were carefully read and classified according to the research questions.

4. Results

By applying the previously described search query and the selection process, shown in Fig. 1, a total of 26 relevant papers were found. A study of these primary works was performed also by pinpointing relevant keywords present in the abstracts (Fig. 2), to find our peculiarities and possible common characteristics. The first general result revealed that all the analysed papers can be grouped into three distinct categories: (a) articles that realized purely data-driven models, (b) articles that followed a fully physics-based methodology, and (c) articles that proposed a combination of the two modelling approaches. The papers belonging to the first category proposed frameworks grounded mostly in machine or deep learning architectures, beginning with the elaboration of literature or proprietary datasets. To the remaining two categories belong two articles that, even though did not always propose any kind of framework or architecture, adopted a data-driven approach to address specific research problems. Table 1 resumes the details of each analysed work by reporting the adopted individual strategies, outlining their working environments, and distinguishing between articles focused on ML or DL solutions. The first category includes eight articles that propose data-driven models, which have shown an increasingly wide use over the last few years. In this regard, Wu et al. [32] proposed a step-by-step framework, in which the DT harnessed fog/cloud computing nodes for diagnostic and prognostics tasks. The presented case study focuses only on the data preprocessing steps and demonstrates how to correctly estimate the RUL of an aircraft engine employing a Recurrent Neural Network (RNN). To the same category belongs the work of Xiong et al. [33], which introduced a similar but less exhaustive framework concentrating on data preprocessing and filtering techniques. The authors evaluated the health status of an aero-engine to predict its RUL by applying the same Deep-Learning method. In Peng et al. [34] the target remained the same: the assessment of turbofan systems. The work aimed at building stable models to create Digital Twins while not proposing any comprehensive framework or architecture. Barkalov et al. [35] instead, described the role of the Digital Twins in socio-economic processes through an architecture, presenting solutions to the RUL estimation and failure forecasting problems. The work focused on the development of a Multi-Task Learning model (MTL). In Heim et al. [36], aircraft maintenance events were exploited through a proprietary platform that provides tools for data visualization and data analysis, by supplying diagnostics information to users in the sector. To this aim,

Table 1
Summary of the information extracted by each paper.

Ref.	Approach	General aim	Specific purpose	ML/DL approach	Sensors	Emulated or real sensors?	Emulated or real model?	Results
[32]	Data-driven approach	Framework for complex engineering products	Estimate the RUL of an aircraft engine	Long Short-Term Memory (LSTM) neural network	Temperature, pressure and speed	Emulated in C-MAPSS software (from NASA)	Emulated environment	Comparison with other literature research methods
[33]	Data-driven approach	Framework for predictive maintenance	Estimate the RUL of an aircraft engine	LSTM	Temperature, pressure and speed	Emulated in C-MAPSS software	Emulated environment	Comparison with other literature research methods
[34]	Data-driven approach	Implementa-tion of a DT, considering model stability	Fault detection of an aircraft engine	–	Throttle position	Emulated in Turbofan Engine System (in MATLAB)	Emulated environment	Definition of an accurate aero-engine model
[35]	Data-driven approach	Use of DT in socio-economic systems	Estimate the RUL of an aircraft engine	Multi-task learning model (MTL)	Temperature, pressure and speed	Emulated in C-MAPSS software	Emulated environment	Comparison with other literature research methods
[36]	Data-driven approach	Framework for predictive maintenance	UI for RUL estimation and visualization of faulty aircraft	Proprietary platform (CORTEX)	No, recorded maintenance events	–	Real applications for users	3D models to give users a look into the aircraft health status
[25]	Data-driven approach	Benefits of Digital Twins	Framework for electrical actuators management	–	–	–	Emulated environment	Design of a DT for predictive maintenance
[37]	Data-driven approach	Structural health monitoring of an aircraft wing	Solutions to load monitor aerodynamic instabilities	LSTM	Strain gauges	Surrogate dataset	Emulated environment	Comparison between the proposed models
[38]	Data-driven approach	Framework for aircraft generator oil temperature prediction	Anomaly detection of the aircraft generator	Random forest	Tempera-ture, speed and load	Real flight data	Emulated environment	Comparison with other ML models
[39]	Data-driven and physics-based approaches	Health monitoring in an electrical power system	Faults detection at the line replace-able units	Adaptive neuro-fuzzy inference system	Speed, torque and stator	Emulated from the physics-based model	Emulated environment	Comparison between the proposed models
[40]	Data-driven and physics-based approaches	Framework for aerospace vehicle reasoning	Description of use case scenarios	–	–	–	–	Frame-work charac-teristics and strong points
[41]	Data-driven and physics-based approaches	Implementa-tion of FAVER framework	Interaction between three aircraft systems	Four ML algorithms	Temperature, pressure, speed and mass flow	Emulated from the physics-based model	Emulated environment and test rig	Comparison with other ML models
[42]	Data-driven and physics-based approaches	Solutions for failures at the landing gear system	Faults classification in an electric braking system model	LSTM	Temperature, brake force, wheel slip, speed and torque	Emulated from the physics-based model	Emulated environment	Comparison with other ML models

(continued on next page)

Table 1 (*continued*).

[43]	Data-driven and physics-based approaches	Implementation of a DT of an aero-engine	Performance monitoring of an aero-engine	LSTM	Temperature, pressure, speed, fuel consumption	Both real and emulated from the physics-based model	Emulated environment	Evaluation of the performance parameter errors
[44]	Data-driven and physics-based approaches	Framework for turbofan health management	Failure mode and failure level identification	LSTM, CNN	Temperature, pressure, speed and mass flow	Both historical and real-time data	Emulated environment	Comparison with other ML models
[45]	Data driven and physics-based approaches	Implementation of a DT of an aero-engine	Detection and isolation of aero-engine faults	Boltzmann machine	Temperature, pressure, speed and mass flow	Real engine simulation data	Emulated environment	Comparison with other ML models
[46]	Data-driven and physics-based approaches	Solution for the aircraft loss of control	Airspeed estimation in case of a Pitot tube failure	–	IMU, GPS, magnetometers and barometric altimeter	Emulated from the physics-based model	Emulated environment	Estimation filter proposal based on extended Kalman filter
[47]	Data-driven and physics-based approaches	Implementation of a DT of an aero-engine	Fault diagnosis of an aero-engine	–	Temperature, pressure, speed, fuel flow	Real data from the TFE731 turbofan engines	Practical implementation in test facilities	Definition of an accurate aero-engine model
[48]	Data driven and physics-based approaches	Round-up of methods for building predictive maintenance systems	Individual analysis of a pneumatic slat drive unit	–	Slat position sensor	Emulated from the physics-based model	Emulated environment	Providing a methodological base for aircraft predictive maintenance
[49]	Data-driven and physics-based approaches	Improve MRO activities	Faults detection in a power electro-nics cooling system	Random forest	Temperature, pressure and mass flow	Emulated from the physics-based model	Emulated environment	Optimal sensor location and sensor types
[50]	Data-driven and physics-based approaches	Implementation of a DT for an aero-engine	Monitor and evaluate performance of an aero-engine	Simple neural network	No, several parameters from the flight data recorder	–	Emulated environment	Definition of a complete DT for aero-engines
[51]	Data-driven and physics-based approaches	Structural health monitoring of an aircraft wing	Wing damage classification and localization	CNN	About 300 sensors on the inboard wing	Emulated from the physics-based model	Emulated environment	Classification results of the CNN models
[52]	Data-driven and physics-based approaches	Structural health monitoring of physical asset	Calculate the degradation of an aircraft wing	CNN, Residual network	12 pose sensors and 12 strain gauges	Real sensors installed	Real environment, with a small-scale aircraft model	Definition of a DT for structural health monitoring
[53]	Physics-based approach	Framework for diagnostics of a fleet of aircraft	Fault classification of aircraft components	–	Pressure	Emulated from the physics-based model	Emulated environment	Comparison between the proposed models
[54]	Physics-based approach	Health management of an aero-engine disk	Monitoring of cracks in the disk	–	Eddy-current, crack angle, key-phasors	Emulated from the physics-based model	Emulated environment	Definition of a DT for an aero-engine disk

(continued on next page)

Table 1 (*continued*).

[55]	Physics-based approach	Aircraft life prediction method embedded into DT framework	Predicting future fatigue cracks of the aircraft	–	Fatigue cracks	Emulated from the physics-based model	Emulated environment	Definition of a DT for RUL evaluation
[56]	Physics-based approach	Full scale verification and validation of the Digital Twin	Fault detection in the environmental control system	–	Temperature, pressure, humidity, rotary position	Real sensors installed	Real environment	Development of a full-scale DT for environmental control system

the platform exposes a DT by implementing a multi-layer perceptron Neural Network, detecting all parts of the aircraft exceeding fault tolerance.

As already analysed in the Related Work Section, the work proposed by Wang et al. [25] presents a preliminary review by investigating and evaluating the quality and stability of appropriate DT techniques in real-world aircraft Maintenance, Repair, and overhaul (MRO) activities. The authors identified two main categories of DT models applied to the MRO sector, i.e., Data-Driven and Model-Based models, and evaluated the applicability of the two models to vehicle system management. The contribution lacks the adoption of data generators, data pre-processing, and feature extraction algorithms.

A different application area involved structural health monitoring practices, as in the work of Candon et al. [37], which presents a comprehensive roundup of data-driven techniques by rigorously introducing the aircraft loads monitoring problem. The DT term was not explicitly used by authors, however, their mission was to predict aerodynamic instabilities that appear on wings and strongly impact the fatigue life of the entire structure. A novelty in the sector was presented by Boulfani et al. [38] who encompass a functional data framework for anomaly detection. Statistical tools for data analysis were exploited for dimensionality reduction to build a DT that served for oil temperature predictions through Machine Learning algorithms.

The relevance of pure physics-based models can be seen in the second category, which includes 4 papers. Zaccaria et al. [53] presented a framework for monitoring, diagnostics, and health management of a fleet of aircraft. Through a signature-based algorithm, the DT of the relative engine was used to reproduce signatures of several main component faults. Although the physics-based nature of the article, a brief sight of Neural Network classifiers was given to show a possible further enhancement. A core component of the turbofan prone to crack failures, the disk, was the main issue presented by Yang et al. [54]. Realizing the digital surrogate of the disk required existing mathematical models and dynamics equations solving. Therefore, an entire physics-based approach based on the study of the vibration response signals was adopted to detect crack failures. The importance of capturing and fusing heterogeneous sources was stated in the work of Wang et al. [55] to produce a life prediction method for aircraft structures. Information such as material propriety and structure geometry, have been fed into the Digital Twin constructed with finite element methods, used for crack simulation purposes. Chowdhury et al. [56] faced the topic of the environmental control system of an aircraft. Their model-based solution was deployed on a real aircraft so that their experimental work was performed directly on the ground test facility.

Finally, the last category includes 14 papers that combine physics-based approaches with data-driven methods. Ezhilarasu et al. [39] focused on health monitoring methods implemented at the aircraft electrical power system level. The Digital Twin of this network, along with its connection to other aircraft subsystems, was built on mathematical fundamentals making use of known simulation tools. The data-driven counterpart was reflected in the development of an Artificial Neural Network (ANN) for isolating faults and predicting their root causes. In another paper published by the same authors [40] an entire framework, FAVER, is proposed. It relies on DT concepts and reasoning techniques, whose goal is to identify, isolate and subsequently predict faults between aircraft subsystems interacting with each other. Some of them were shown for demonstration, proposing a DT based both on physics and data-driven modelling. Authors presented the various use cases following a common line in a separate article [41]. Two of the three use cases were represented by simulation models, while the last one followed a more efficient approach by performing hardware-in-the-loop tests. A crucial aspect of the adopted solutions relied upon the exploitation of the Open System Architecture for Condition-Based Monitoring (OSA-CBM) specification, which resulted in applying algorithms for data manipulation and defining the state detection and health assessment steps as a faults classification problem. Another critical component, the aircraft landing gear, was presented by Ramesh et al. [42] by taking an already existing electric braking system model as the Digital Twin. Employing a physics-based approach obtained with the aid of a software environment certain types of faults were simulated. In addition, this work presented a solution using a Recurrent Neural Network for correctly identifying these failures. The turbofan returned to be the main topic in the work of Liu et al. [43]. The solution proposed by the authors is based on the data fusion concept, by merging data obtained from the physics-based model and the data-driven one, to achieve an accurate performance monitoring of the aero-engine. A similar but enhanced approach is described by Zhou et al. [44] that aimed at assessing the real-time health status of the turbofan. The work proposed the adoption of visualization tools for displaying the DT and a Convolutional Neural Network (CNN) for analysing its output data. Huang et al. [45] discussed a different perspective on information fusion from the physics-based and data-driven models by implementing feed-forward and Recurrent Neural Networks. The purpose was to form an improved version of a DT for real-time fault detection of an aero-engine by constructing a degradation adaptive correction model. Alvarez et al. [46]

suggested a solution for another individual problem that involved aircraft airspeed estimation whenever a failure in the Pitot tube sensor occurred. After representing the specific sensor by physics-based simulation models, particular attention was paid to the data fusion and estimation techniques. Peng et al. [47] organized their project around the aero-engine as well, in a practical test facility. Through a novel and efficient algorithm used for system identification, authors combined the physics-based and the statistical data-driven approaches for performing fault diagnosis. A similar combined use has been proposed by Smagin et al. [48] for predicting the failure of aircraft units. Statistical and classification methods are mentioned, however particular emphasis has been given to the definition of a mathematical model to represent a DT for the aircraft slat drive unit. Apostolidis et al. [49] focused on the criticality of the cooling system of an aircraft. The objective of the study is to develop a framework to determine the optimal physical location and type of sensors in the cooling subsystem. Three different modelling concepts were designed based on the laws of physics and ensemble learning methods. Furthermore, Liu et al. [50] worked on data fusion methods and both model-driven and data-driven approaches were chosen. In building the Digital Twin, the authors focused the attention on the data pre-processing and feature extraction steps on flight recorded data, with the aim of applying accurate monitoring and performance evaluation of the aero-engine. The structural health monitoring of an aeroplane wing was the main topic Lin et al. [51] dealt with. The authors proposed a comprehensive framework that could be divided into four steps. The first two involved physics-based approaches by performing aerodynamic analysis and by modelling the wing with finite element methods. The remaining two steps are data pre-processing data transformation into grayscale images to use a Convolutional Neural Network (CNN) for damage classification and localization purposes. Analogously, Lai et al. [52] presented a multi-step DT process for structural health monitoring. It exploited an example (i.e., aircraft wings) to conduct a finite element analysis to create AI-driven load identification models, AI-driven load identification methods, and use surrogate models for performance prediction. For each objective, authors provide a web interface and a graphic library to researchers interested in the exploitation of the presented methods.

5. Discussion

The analysis of the 26 primary works highlighted some common uses in both adopted software tools and modelled subsystems. This discussion aims to answer the research questions and support researchers and practitioners with a modular architecture extracted from primary works.

RQ1: Is there a preferred approach and which software tools are used for building digital twins in the field of maintenance, due to failures in the aircraft components?

This subsection identifies the trends in terms of software tools used in DT solutions for aircraft subsystems. To this objective, the papers are grouped into two categories based on the adopted modelling approach: physics-based or data-driven.

Starting from the 18 articles focused on physics-based approaches, their Digital Twins usually capture existing knowledge by applying classical mechanics [57] to have universal validity. Nevertheless, such models exploit computationally intensive procedures and limitations can arise in real-time domains [58]. Various programming tools are usually used by the authors to support such systems. The most important ones include LabVIEW [59], SolidWorks [60], ANSYS [61], Simcenter Amesim [62], and the MATLAB [63] suite with Simulink. LabVIEW is a graphical programming environment that can be used for data acquisition and data visualization [56]. Additionally, it can be integrated into a DT architecture by supporting the creation of a Human Machine Interface (HMI) to show the assets of interest, such as the motor properties, and through a specific add-on, to provide a real-time tool for online diagnosis monitoring [47]. SolidWorks instead belongs to computer-aided technologies, among which computer-aided design is one of the most used methods for solid modelling of key components. For instance, in the work presented by [54], it is used to propose a DT solution focused on an aero-engine disk model that collected vibration data under different conditions. ANSYS is a high-fidelity software that allows for executing finite element analysis. To this end, the program can be used to split the complex structure of the aircraft component into several small pieces connected to form a mesh. For instance, reducing the number of physical prototypes and experiments can allow identifying the stress concentration of an aircraft structure and contributes to extract information useful for RUL prediction purposes [55]. Other similar functionalities are also used for calculating approximate solutions by simulating strain distributions that affect the composite wing of an aeroplane [51]. Another main contribution to the development of model-driven implementations was obtained by using the Simcenter Amesim software. It essentially provides a mechatronic simulation platform that boosts the overall engineering productivity, by providing a comprehensive understanding for designing and simulating pneumatic systems and components. Hence, it is suitable for building a slat actuator model which provides the calculation of aerodynamic loads acting on them and their possibility of failure [48]. Nevertheless, the MATLAB platform combined with the Simulink environment is the most widespread in academia [63]. Simulink provides a graphical editor for creating block diagrams that visually represent the models. In this way, Digital Twins of aircraft subsystems can be constructed with a high level of detail allowing the collection of simulation data both under healthy and faulty conditions [39,42,46]. By leveraging additional toolboxes, multi-domain physical models can be simulated [43,44] optionally integrating external reasoning layers [40,41]. Some other works also describe solutions exploiting physics-based models [45,49,50,52,53], however, they do not provide readers with details on the adopted software tools.

Alternatively, as already discussed, the second approach is the data-driven one, which has gained momentum in the last few years thanks to a combination of factors, among which is the improvement of computer technologies and artificial intelligence. This led to an increased proposal of Machine Learning applications, although not strictly necessary to realize data-driven solutions. Different tools and frameworks have been exploited by the primary works that adopt this approach, and the most spread ones

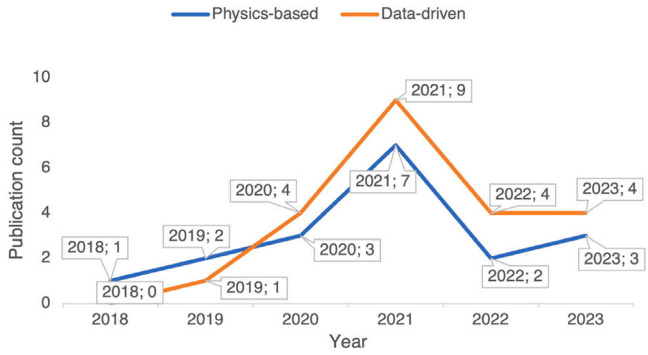

Fig. 3. Number of publications per year.

are: TensorFlow [64], OnPoint CORTEX [65] and MATLAB [63]. The TensorFlow framework is a flexible ecosystem of tools that significantly accelerates the development of machine learning models. Therewith, algorithms for building the multi-task learning model can be implemented, representing a valid solution for the forecasting part [35] of a Digital Twin. In contrast, CORTEX is an industrial platform that offers a variety of proprietary algorithms. Within a DT architecture, it also contributes to visually representing the state of the aircraft [36]. Moreover, even for the studies that involved both physics-based and data-driven approaches, the MATLAB platform is also usually used for the data-driven part [25,46]: it supports the collection of required output data by providing specific inputs [34] but also provides blocks for feature selection or for supervised machine learning exploration using various classifiers [40,41]. The MATLAB platform can host many toolboxes for developing machine learning models, allowing the building of Artificial [39] or Recurrent Neural Networks [42]. In addition, also in this case, some works did not provide detailed information on adopted tools or platforms. Some of them exploit unmentioned Cloud and web services for storage or deployment purposes [32], some others were instead more focused on the Digital Twins rather than the individual tools used for its implementation [33,43,47–50]; others, instead, focus their attention on the results obtained by the application of DT and compare diverse Machine or Deep Learning models [37,38,44,45,52], or the accuracy of the same models applied to different datasets [51].

In summary, on the one hand, physics-based solutions usually exploit tools for designing the system and test them through graphical interfaces used as support for measurements. On the other hand, the solutions based on the data-driven approach focused more on the services and the benefits provided by Digital Twins rather than the adopted technologies. However, there is not a clear separation among the works focused on the first or the second approach and there is not a clear trend in the last few years. In fact, by counting the publications over the years, as shown in Fig. 3, there is not an evident predominance. However, in the last few years, a slight propensity towards data-driven methods can be observed.

RQ2: What safety-critical components of an aircraft prone to failures are covered and which kind of approach is preferred for each topic?

The analysed articles differently treat and mention the various subsystems and components of the aircraft. Some of them, for instance, provide a comprehensive overview of the context to discuss each of them [36,55]. To summarize, as depicted in Fig. 4 thirteen distinct safety-critical aircraft components have been identified as the most interesting for researchers, practitioners, and experts of the domain, namely: disk, environmental control system, engine, fuel system, general structure, electrical power system, cooling system, electric braking system, air data system, slat drive unit, wings, generator and the electrical actuation system. All of them are almost equally treated in the analysed works and none of them seems to be more investigated than the others. As a further interesting result, Fig. 4 presents a diagram that shows how almost all the components are presented and discussed in the primary works belonging to both the data-driven and physics-based approach, but the thickness of the lines highlights the different importance given to each component by the two approaches.

One of the most critical components is undoubtedly the wings since aerodynamic loads that occur on them could affect the entire airframe structure [37] or the wings themselves [51,52]. Other components that could be affected by malfunctions are the fuel system, due to the large use of pumps, the line replaceable units, which have the critical task of connecting the electrical power system with other components [39], the environmental control system, and the valves. By considering the environmental control system that, for instance, regulates and mitigates the airflow in the aircraft, in fact, it is responsible for the comfort of all the passengers and the proper functioning of the onboard equipment [56]. Furthermore, any malfunction occurring in the fuel system would lead to safety issues [40,41]. Instead, a less dangerous, but not less important, component is the power cooling system, which could cause aircraft issues only when the aircraft is on the ground [49]. These problems could be encountered whenever the generator overheats or has a very low oil temperature [38]. The landing gear is an additional safety-critical system, in fact, it includes the braking unit and possible malfunctions would be potentially catastrophic and the aircraft could skid off the runway [42]. On another hand, the air data system is the component that is responsible for the flight parameters estimation for performing safe aircraft operations. Another key element of the system is the pitot tube sensor, responsible for evaluating the airspeed and is susceptible to

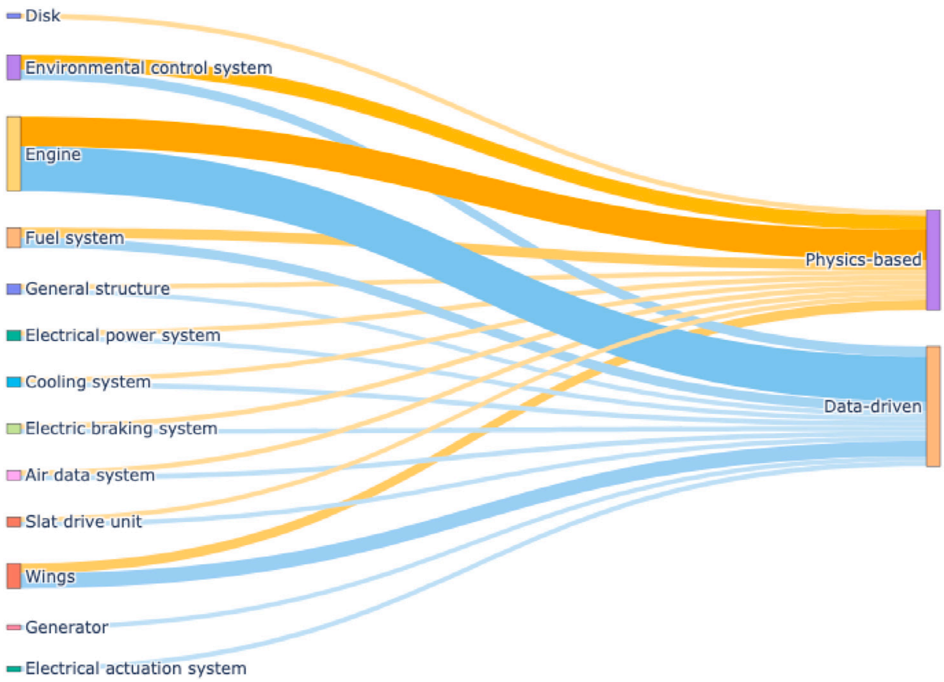

Fig. 4. The Sankey diagram of the aircraft components that describes the contribution of each component to the two identified approaches.

adverse weather conditions causing unreliable calculations [46]. Specifically, aerodynamic loads act also on slat pneumatic actuators of an aircraft [48] and other failures can occur at the component level in electro-mechanical and electro-hydro-static actuators [25]. The aero-engine disk is another part that has to be monitored, due to possible damages that can be suffered [54]. Finally, the most important block of an aircraft is its engine, the turbofan, and all its sub-components, such as the fan, the low-pressure compressor, the high-pressure compressor, the low-pressure turbine, and the high-pressure turbine [32–35,43–45,47,50,53].

RQ3: What type of knowledge can be extracted to design a data-driven modular architecture?

After a comprehensive study and analysis of the primary works, the reference modular architecture shown in Fig. 5 has been extracted as a summary able to represent all the reviewed papers through services and features that this research declared to be really important for the sector. Being inspired by existing well-known architectures, including the Dynamic Data Driven Applications Systems framework that can play a role in Digital Twins [66], our proposed architecture is organized in blocks, each of which has its functionality and participates in the construction of a Digital Twin for the predictive maintenance of aircraft.

The blue module is the one related to the IoT technologies and includes the "Data acquisition" component. It is responsible for collecting data from target assets through real sensors, according to the guidelines of IoT architectural standards such as IoT-A [67], or from existing or enhanced datasets, as done in most of the primary works. In the absence of real data, maintenance records or design documents are exploited [41]. For physics-based solutions, such a component could be also responsible for allowing the collection of synthetic data generated by simulation tools. In fact, in general, the simulation tools, in both kinematic and structural modelling, enable designers to define virtual sensors aiming at monitoring and gathering data during the simulation. From this point of view, our proposed architecture serves as a unifying approach that equates IoT-based DTs for aircraft maintenance and physics-based DTs by putting them on the same level, as shown at the top of Fig. 5 (purple and water-green modules). The proposed approach has various advantages: (i) its extent is general enough to be used in all aircraft maintenance data-driven processes (both for data extracted from physics-based simulators and data gathered from the field through IoT sensors or humans/tools in charge of operations); (ii) it incorporates a typical Machine Learning pipeline leveraging on existing Information Technology and Cloud infrastructures; and (iii) its modular structure isolates the domain-specific part within the Data Preprocessing, Feature Extraction, and ML/DL Model blocks. As we demonstrated by reviewing the state of the art, different maintenance operations generate diverse data. This means that different ML/DL models must be hosted to work on diverse datasets. Following this perspective, the link between DTs and the IoT paradigm gives a strong basis to two convergence processes: (i) the integration of DTs physics-based and DTs data-driven as the reviewed articles reveal, and that is a path common to other industrial domains [68]; (ii) the converge between IT-based and OT-based (Operation Technology-based) maintenance tasks that are frequent in smart-manufacturing frameworks and that recognizes the data as playing a central role [69].

The "Data Preprocessing" block (in green) is responsible for data filtering, data transformation, and data completion where samples are missing. Due to the different operating conditions, it is appropriate to remove noise artifacts [32], since the quality and

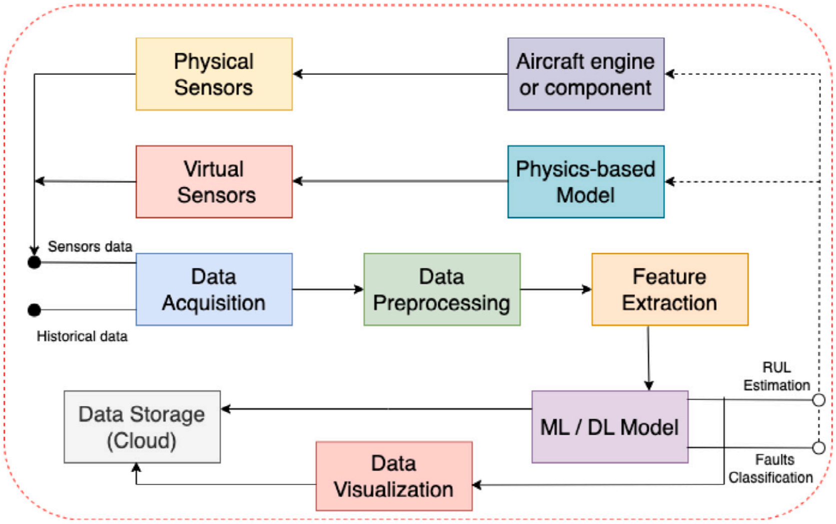

Fig. 5. The proposed modular architecture.

the format of the data highly influence the correct operation of every Digital Twin solution. Nonetheless, such filtration is differently performed by each author. For some authors, for instance, the normalization (the process that makes data "standard" with respect to the one that has to be treated by the system) is one of the mandatory processes to be performed in the "Data Preprocessing" stage, whereas others prefer de-noising techniques or clustering algorithms.

The "Feature Extraction" block is responsible for extracting the data that are more relevant for the algorithms that will be used for the predictions. It also enables the reduction of the data dimension to the computational complexity [32]. In such a block, specific techniques are usually applied, such as the Minimum Redundancy-Maximum Relevance one or the degradation models that are typically applied when the final goal is to predict the RUL of a particular component.

Moreover, the ML/DL block represents the core component of the Digital Twin solutions. Based on the analysed literature, two different techniques are usually preferred for this block: the first one exploits Deep Learning models, based on Long Short-Term Memory (LSTM), an RNN model that deals with time series information to learn the complex rules in a considerably long period [33,42], to classify faults or predict RUL of components; the second one, instead, is based on Machine Learning techniques, that are preferred when the data-driven approach is used in combination with physics-based methods, such as the Random Forest classifier that is frequently used in fault detection [49]. This module could be also extended to support Reinforcement Learning techniques.

Another block that has been inserted in our architecture is the "Data Storage (Cloud)" because a cloud infrastructure is essential to setup and maintain Digital Twins. This component groups all the services that are deployed on the cloud to serve as data storage, but also orchestrator of a large part of the data operations; also the DT itself can be deployed on these services [32].

Finally, a "Data Visualization" component has been inserted in the architecture although few of the analysed works exploited such a similar block. The reason resides in the usefulness of the proposed Graphical User Interface that can provide actionable insights allowing the optimization of processes [36] by simply entering aircraft information, like the identification of the components with high failure probability.

All the presented components and, therefore, the architecture itself, have been designed as stand-alone modules that can be activated and deactivated by researchers to promote, for instance, the experimentation of different alternative solutions within the same testing environment. Thanks to this modular nature, in fact, all the analysed data-driven solutions could fit into this architecture and, as a result, could execute their experiments without re-implementing all the developed infrastructure. It is specifically highlighted in Table 2 that reports a mapping among the identified most important existing tools and the blocks of the architecture that they already cover through their software.

RQ4: What are the open issues to be further investigated?

The adoption of the proposed architecture to real applications of DTs for aircraft maintenance could lead to some drawbacks that we grouped into five subsections.

5.0.1. Availability of literature datasets

Despite the advent of Big Data, the growth of data-driven solutions must challenge the scarcity of datasets with run-to-failure trajectories. This is due to a couple of reasons: the rarity of failures occurring in real aircraft leads to the lack of labelled data (they usually lack time-to-failure labels). In addition, the dataset owners sometimes are reluctant to share their results. Therefore, in recent years NASA researchers have started to collect data in a new realistic large dataset [70], that will provide the scientific community with an important but initial artifact to work on.

Table 2
Mapping among existing tools and the proposed architecture's components.

Tool	Architecture component(s)
LabVIEW [59]	Data acquisition, Data Visualization
SolidWorks [60]	Physics-based Model
ANSYS [61]	Physics-based Model
Simcenter Amesim [62]	Physics-based Model
MATLAB & Simulink [63]	Physics-based Model, Data Acquisition, Feature Extraction, ML/DL Model
Tensorflow [64]	ML/DL Model
OnPoint CORTEX [65]	Data Acquisition, Data Visualization, ML/DL Model

5.0.2. The lack of internet of things support

Although IoT for data acquisition is applied in many manufacturing areas, there is a lack of adoption in the aircraft domain. The reason lies on the hardware side: the limited number of sensors due to several aircraft constraints [53] does not allow to perform comprehensive data analytics [49]. Moreover, the possible solution developed for a specific type of aircraft cannot be applied to other ones.

5.0.3. Real-time decisions on the edge architecture

Another important issue to be considered is the need to make autonomous decisions at the edge level to detect, for instance, faults in real time. Such elements could help pilots in adopting the proper countermeasures, e.g., changing the flight profile. However, at the moment of writing experimental components that hosts AI-based algorithms able to support pilot decisions are still in their early stage and we hope this will stimulate more research in the area.

5.0.4. Maintaining the Digital Twin

One acknowledged challenge in the DT field that researchers have to face is related to the choice of the "right" time to update the Digital Twins [71]. In fact, in the case of DT that are not up-to-date, some issues can affect the entire ecosystems served by the DT itself. For instance, the misaligned DT can cause potential deterioration of an aircraft component or can lead to data pattern changes causing performance worsening [32]. Correspondingly, a further study on the domain adaption field for conforming models across source and target domains fits also in this context.

5.0.5. Explainability of deep neural networks

A technical aspect that should be taken into consideration concerns the scepticism about DL methods which can result in certification issues for MRO organizations [49]. Hence, while some authors prefer to adopt algorithms based on conventional decision and fault classification trees, in literature new research opportunities are emerging for adopting explainable AI in predictive maintenance, by using Deep Neural Networks [72].

6. Conclusion

Digital Twin solutions are becoming essential in today's industry. As an IoT evolution, by replicating the planned production process and reporting information from the real world thanks to IoT sensors, the Digital Twin allows engineers to identify process errors before the product goes into production. This is crucial to support the digital transition of various sectors following the Industry 4.0 paradigm. Nonetheless, the full potential of DT is still unexpressed. In this paper, through a systematic review, we gave scientific ground to this statement in the aerospace industrial sector, in particular for the aircraft maintenance processes.

By following this approach, from a collection of 2472 existing works 26 primary papers were extracted, after an accurate analysis and filtering of the state of the art. Each analysed work, which was published in the time window between January 2018 and July 2023, guided the discussion that provided detailed answers to four Research Questions. As a first step, the works were grouped into two different categories based on the chosen modelling approach, and for each of them, the main adopted software tools were identified. The presented results highlighted a slight predominance of the data-driven approach, which is more focused on the services and the benefits that the DT provides, in contrast to the physic-based one that relies on designing and testing tools. By applying the same categorization, we also seized the opportunity to focus on the aircraft subsystems that involved Digital Twins technologies. Based on the analysed information, eleven specific aircraft components were covered with no full-blown preference for the debated topic or the followed modelling methodology. All the acquired knowledge has supported the full comprehension of the specific research subjects and assisted authors in the extraction of a modular architecture, as a summarizing proposal able to represent all the analysed works through services and features that these works declared to be really important for the sector. By taking inspiration from well-known patterns, the architecture has been designed as a set of stand-alone modules involved in the process of creating the Digital Twin for the predictive maintenance of aircraft. Finally, some interesting hints for the research community have been highlighted as open issues that will need further investigation. The identified open points involve 5 distinct aspects: Big Data, IoT, Edge Computing, the DT itself and the Deep Neural Networks. Among them the lack of appropriate IoT support for Digital Twins for the predictive maintenance emerges as predominant, and, therefore, our proposed modular architecture empowers the IoT role following architectural standards. From a practical point of view, the modular architecture allows practitioners, experts, and researchers operating in the domain to concentrate their effort only on some specific components, that, for instance, can be activated and deactivated to experiment with different alternative solutions and to collaborate with other stakeholders that are instead interested in other components to contribute to the whole DT for aircraft maintenance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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