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Digital Twin Architecture for a Sustainable Control System in Aircraft Engines

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Abstract

Over the past decades, climate change has remained one of the major global challenges in the world. In the aviation and aerospace industry, the environmental sustainable development strategies towards carbon-neutral mainly focus on efficiency and demand measures, sustainable fuels, renewable energies, and removal and carbon offsetting. The carbon dioxide equivalent (CO2e) emissions footprint of an aircraft is primarily determined by energy and fuel efficiency. The advanced engine control systems of an aircraft can optimise the engine performance to achieve energy efficiency, fuel optimal consumption, and emission reduction. This paper proposed a digital twin architecture of a sustainable aircraft control system that allows the system to collect, analyse and optimise sustainability-related data and to provide insight to operators, engineers, maintainers, and designers. The required information, knowledge and insight databases across flight environment, engine specification and gas emissions are identified. The research argued that the proposed architecture could enhance engine energy efficiency, fuel consumption, and CO2e footprint reduction and enable (near) real-time data monitoring, proactive anomaly detection, forecasting, and intelligent decision-making within an automated sustainability control system. This research suggests ontology-based digital twin as an effective approach to further develop a cognitive twin that facilitates automated decision-making within the aircraft control system.

Keywords: Digital twin, Control System, Fuel Efficiency, Sustainability, Aircraft Engine, Ontology, Sustainable Aviation

1. Introduction

Since the late ’90s, gradual developments in computer science, data analytics, modelling and simulation techniques reduced the dependencies on traditional, time-consuming, and costly physical testing equipment for complex engineering assets [1]. High-value industries historically prioritised commercial gains and performance-driven asset value creation. However, over the last decade, they have been impacted by environmental concerns and several obligations to reduce their emissions and carbon footprint. The application of modelling and simulation techniques in the aviation industry have been studied to enhance fuel efficiency with the aim of enhancing thermal cycle efficiency [2]–[4]. The aviation industry is projected to experience continuous growth, particularly in passenger air traffic, at an annual rate of 4.7% [5]. This growth is anticipated to contribute to global environmental concerns at national and international levels, including climate change and CO2 emissions. Despite improvements in fuel efficiency, the aviation industry is facing a critical environmental crisis, currently contributing to 2.5% of global CO2 emissions (i.e., roughly 1 billion tons of CO2 per year) [6]. The industry has set ambitious goals to reduce emissions to half of 2005 levels by 2050 and improve fuel efficiency by investing in green alternative fuels [7]. The requirement for continuous efficiency improvements relies on technological strategies such as aircraft weight reduction (using lighter and more wear-resistant materials), engine propulsion (thermodynamic and propulsive) efficiency and aerodynamic (drag reduction) improvements. The adoption of aerodynamic strategies to reduce the environmental impact of the aerospace industry optimises state-of-the-art aerodynamic technologies and tools for improving aerodynamic efficiency, devices that have an inherent potential to improve efficiency [8].

1.1. Sustainable Aviation Industry

Sustainability is seen as being at the core of business strategy, as highlighted at the United Nations Conference on Sustainable Development 2030, which includes smart manufacturing, energy-efficient buildings, and low-impact industrialisation [9]. In the aviation industry, fuel efficiency and Sustainable Aviation Fuel (SAF) are the most critical approaches towards decarbonisation and sustainable aviation. SAF is made from waste and other residue fats, oils, and gases and produced through the hydro-processing of esters fatty acids known as HEFA. Currently, most certified SAFs can be blended with conventional fossil jet fuel up to 50% [10]. Modelling the behaviour of energy consumption is the first step in monitoring and reducing energy consumption. However, it requires an in-depth understanding of the motion and dynamic behaviour of the system [11]. Besides, electrification of the engine fuel pumping system is a priority issue due to the contribution of the engine's power generation structure to the reduction of fuel consumption. A multi-physical field coupled model is required to numerically simulate the heat dissipation characteristics of the housing under typical operating conditions. On the one hand, the heat generated by motor losses should be reduced. On the other hand, the heat dissipation capacity of the motor should be improved as much as possible from the perspective of cooling performance [12]. Decarbonisation and reducing environmental impact are necessary for a sustainable future in the industry. The key approaches towards sustainable aviation are presented in Figure 1.

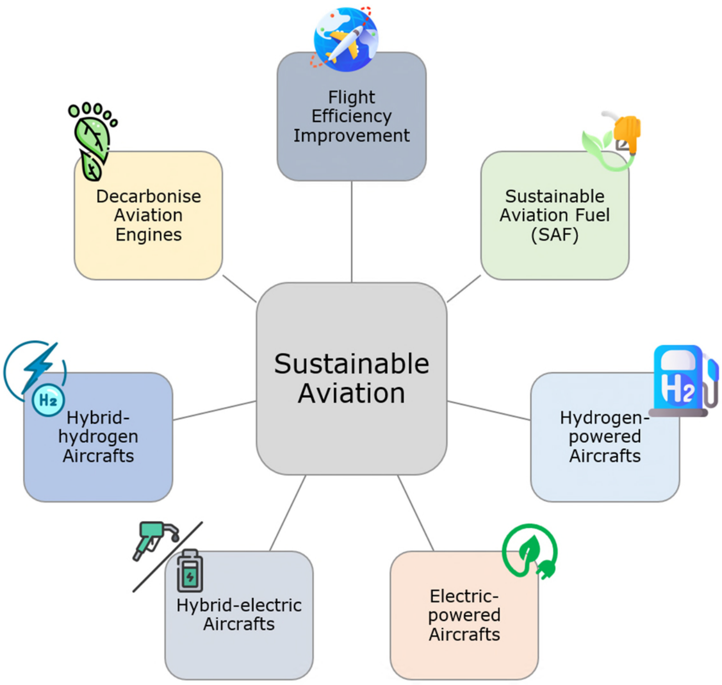


Figure 1. Sustainable aviation

The developments in modelling and simulation approaches enable a more accurate representation of systems as well as a prediction of the systems' behaviour. These led to the idea of connecting the virtual space to the real world through the concept of 'Digital Twin' [13]. The rapid development of simulation technology has pushed the boundaries from purely model-based numerical simulations such as large eddy simulations (LES) and Reynolds-Averaged Navier Stokes (RANS) to hybrid modelling utilizing experimental data and physical laws [14]. Data-driven methods are a new modelling paradigm that addresses the problem in complex system and process modelling since it can directly create the mapping between engine input and output using collected or streaming data without explicit model construction. It has shown great potential in statics analysis for fluid dynamics, engine system identification, fuel efficiency, and health monitoring because of its capability for high-dimensional non-linear function approximation and general data interpolation [15]. Later, with the great leap in sensing technology like the Internet of Things (IoT), this concept of bridging physical sensors with actuators and digital decision-making modules with controllers is expected to be realized for an industrial application [16], [17].

1.2. Digital Twin Technologies and Sustainability

Digital Twin (DT) technologies are seen as a major contributor to automation, digital manufacturing, and sustainability. Grieves [18] defined DT with three elements: a physical product in the real space, a high-fidelity virtual product in the virtual space, and a connection that ties these two spaces together. In the scientific literature, there are several definitions of DT. Recently, ISO 23247-1:2021 defined DT in the manufacturing domain as a fit-for-purpose digital representation of an observable manufacturing element with synchronization between the element and its digital representation. However, to include a broader range of applications, a DT can be defined as a dynamic digital representation of a real entity [19]. During the Industry 4.0 era, researchers and practitioners are seeking a flexible and intelligent solution for smart energy systems. Ardebili et al. [20] suggested that DT can make energy systems intelligent in decision-making and provide dynamic monitoring capability for anomaly detection and demand forecasting [20]. The DT models can provide a method for self-monitoring sustainable development [21]. Moreover, DTs can enhance visualisation and allow end users to select the appropriate strategy in accordance with the specified sustainability goals [22]. Combined simulation platforms for engines and high-value asset equipment can be used to assess and optimize the energy distribution and performance of future vehicles with different technologies or strategies. These will provide a theoretical basis and numerical modelling support for the development of energy-efficient technologies [23].

Digital twin technology has been widely implemented in various industries, including automotive, manufacturing, building and aircraft, to reduce carbon and environmental footprints by improving energy management, maintenance, energy-efficient design, and integration with renewable energy sources [24], [25]. In manufacturing, simulation modelling and DT technology have been widely used to analyse and improve system performance [26]. Franciosi et al. [27] observed increasing interest in using DT technology for sustainable industrial maintenance and production, with a focus on the economic aspect. Energy cost and efficiency are commonly studied, while pollutant-related criteria, such as carbon/CO2 emissions and waste generation, receive less attention. Alford et al. [28] explored the potential of flexible DTs to drive energy efficiency and decarbonisation in process industries. They introduced a layered DT approach, combining different tools to create a self-optimising and self-learning virtual plant. Combining energy-efficient technologies with smart and digital technologies can solve the problem of energy consumption [29]. Li et al. [23] suggested that for high-value assets such as engines, combined DT and simulation platforms can be used to assess and optimize energy distribution. Such an approach can provide a theoretical basis and numerical modelling support systems for the development of energy-efficient technologies [23].

Digital twin-driven product design helps to close the gap between the product's physical and virtual spaces, which decreases the efficiency and sustainability of the design, manufacturing, and service. Web-based digital twin architectures have enormous potential to contribute to the sustainability of industrial cyber-physical systems. Data-sharing and collaboration enabled through the DT technology create opportunities for companies to improve sustainability performance, even on legacy assets [30]. Ezhilarasu et al. [31] concluded that in the current climate, the main problem with the management approach to aircraft health is the inflated cost of efficiency. They believed that the cascading effect of aircraft would be mitigated by building DT technologies for aircraft and creating a unified system architecture for isolating faults [31].

1.3. Contribution to Knowledge

The DT model of a sustainable control system in aircraft engines can be described as a digital copy of the control system in a virtual environment that enables (near) real-time monitoring and restricting engine emission (CO, NOx, etc.) and system running state followed by decision automation and system adaptive control [32]. Such a DT model allows the control system to be self-aware of its current state and adapt to external changes dynamically. A schematic model of an aircraft engine, the critical modules and the allocation of the current control system is presented in Figure 2. The critical modules include the High Pressure (HP), Intermediate Pressure (IP) and Low Pressure (LP) sub-systems. The primary role of the engine control system is to provide the suitable amount of fuel needed for the engine to produce the desired power based on the pilot's power request and maintain the engine power at the desired level in the presence of airflow disturbance and changes in flight conditions. It is evident that ensuring an engine's sustainability and efficiency relies on a wide range of data and information encompassing the operational environment, engine's specifications and health condition. This requirement presents the prevalent challenge of inadequate data availability and quality to support the sustainability and efficiency targets in the aviation industry. This paper suggests the application of DT technology as a promising approach to overcome this challenge. This vision is supported by a systematic literature review and experts' insight in this paper.

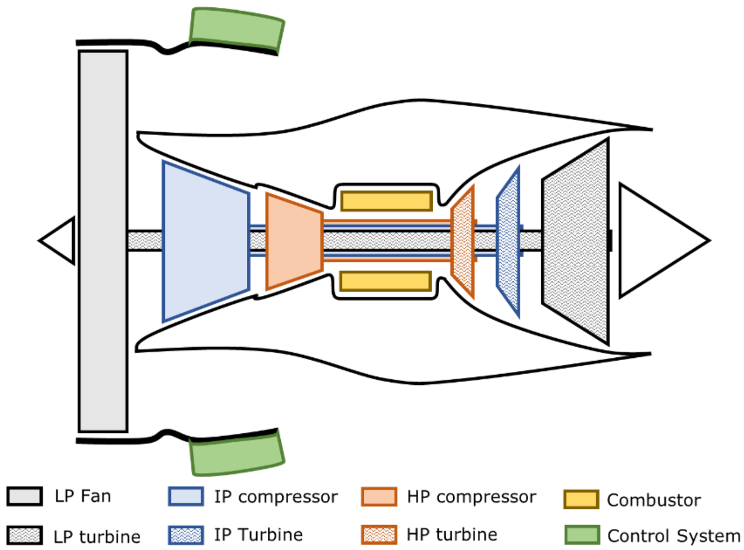


Figure 2. Aircraft engine and its critical components

In this paper, the DT architecture of a sustainable control system for an aircraft engine is presented. This study attempted to answer the following research question: How can DT assist with improving engine sustainability and efficiency in the aviation industry? The paper is organized as follows: Section 2. presents the state-of-the-art regarding DT designs, sustainability and fuel efficiency in complex engineering assets using a systematic review approach. The research methodology and the overview of the analysis of the methods used in this research to develop the DT architecture are presented in Section 3. The proposed digital twin architecture is presented in Section 4. This is followed by discussions in Section 5 and conclusions and further work in Section 6.

2. State-of-the-art

2.1. Digital Twin Technologies

Digital twin (DT) is known as one of the emerging technologies within the industry and construction sectors as an effective approach for improving energy efficiency and management [33]. The use of DT and Artificial Intelligence (AI) technologies in energy consumption and efficiency have been studied recently, focusing on effective energy management for buildings [34], [35] and electric vehicles [36], energy efficiency in hydraulic systems [37], energy efficiency and maintenance in smart manufacturing systems, and carbon footprint assessment in smart cities [38]. DT technology is endowed with a value system that enables it to make autonomous decisions. Such capability can be used to promote sustainable energy consumption in ecosystems [39]. Barykin et al. [40] introduced an energy-efficient network topology for digital omnichannel marketing. The network consists of nodes representing participants with unique characteristics, creating a digital customer value network. The authors developed omnichannel interaction algorithms that incorporate economic indicators, enabling the use of DTs within the ecosystem. Assad et al. [41] proposed that Web-Based Digital Twins (WDTs) have enormous potential to contribute to sustainability by accessing control parameters that affect energy consumption, recording energy consumption data, and making predictions through computational algorithms [41]. Later, Zhao et al. [42] analysed the development modes of a DT system, including symbiosis, evolution, and optimization and proposed the key technologies of a DT for an integrated energy management system [42]. In addition, Sun et al. [43] developed a deep learning model based on graph neural networks (GNN) to predict physical states and thermodynamic characteristics in supercritical CO2 power generation systems. The model outperformed traditional machine learning models.

In manufacturing, the DT-driven optimisation approach enables the smart manufacturing of aerospace generators with a high number of system components through the virtual-real combination of system performance and manufacturing. In such applications, the DT model receives real-time data from manufacturing measurements and feedback to the key performance indicators, which are corrected throughout the optimisation process [44]. Moreover, DT can be applied to optimise energy efficiency in manufacturing systems. In that case, data can be collected in real-time from analogue physical systems and transferred to digital systems. Then, energy-saving strategies and key monitoring metrics can be realised in the digital space. Afterwards, he generated energy-saving instructions that can be sent to the analogue manufacturing system in the physical space and control the energy consumption [45]. Zhang et al. [13] proposed a framework for equipment energy consumption management in a digital twin shop floor to reduce energy consumption and improve the energy efficiency of equipment on the shop floor. They argued that the digital twin shop-floor environment could be used to explore the potential applications of equipment energy consumption management under three categories: energy consumption monitoring, energy consumption analysis and energy consumption optimisation. Li et al. [46] developed a data-driven DT model for monitoring and controlling the energy behaviour of equipment in manufacturing. The model combines Petri-net modelling and machine learning techniques and utilises real-time data on working conditions, operating parameters, and production load to enhance the energy management capacity of the DT. In a more recent study, Krommes & Tomaschko [47] proposed a DT framework for value and material flow when monitoring energy and material flows. The framework proposed solutions for allocating energy consumption and setting peak energy savings.

2.2. Digital Twin Applications

The application of DT technologies for energy efficiency of data centres has been investigated by several researchers. Tang et al. [45] highlighted that the implementation of DT technology is crucial for achieving the standardization and modularization of industrial data infrastructures, resulting in significant energy savings for data centres. By adopting DT, traditional industries can transform into energy-efficient sectors aligned with the advancements of Industry 4.0. This transition not only enhances industrial energy efficiency but also extends the scope of innovative technologies in this domain [45]. Similarly, Dongyun et al. [48] proposed an intelligent online operation and maintenance system based on DT and industrial internet technologies for real-time monitoring and management of equipment and the operational status of hydrogen energy production and storage power plants. Their proposed architecture considers the virtual model of a physical power plant, visual display, status evaluation, information viewing, traceability, optimization, and statistical analysis. Moreover, Zinting et al. [49] proposed an energy-saving solution using Artificial Intelligence (AI) and DT for a smart data centre. Their work concluded that the DT model can reduce energy consumption by optimising the cooling system.

The application of DT technology for evaluating sustainability and energy consumption in high-value and complex engineering assets has been studied recently. It is crucial for the DT models to access the control parameters affecting energy consumption and to record the energy consumption [41]. Passath et al. [50] present the application of DT technology for combined critical value assessment and RAMS2 (Reliability, Availability, Maintainability, Safety and Sustainability) over assets' life cycle. Deon et al. [51] proposed a DT architecture based on a decision support system for real-time predictive maintenance and fault classification in thermal generation engines. The architecture integrated machine learning models and fault classification algorithms into the plant's control system, enabling operators to receive timely alerts and insights. A DT methodology using Computational Fluid Dynamics (CFD) analysis is proposed by Gebauer et al. [52] proposed a DT methodology using Computational Fluid Dynamics to optimise the cooling of induction motors. The proposed DT minimised losses and maximised efficiency by considering complex geometry and asymmetric flow caused by the rotating fan. Several studies focused on the application of modelling and simulation to predict the performance of critical components in a gas turbine, in particular [53] [54]. Xin et al. [55] focused on the application of DT technologies for the design of gas turbines. They suggested that the DT model can improve the efficiency of design data transmission and establish a large database for test evaluation. Sciatti et al. [56] developed a Simulink-based simulation model for the fuel system in aircraft gas turbine engines. The system's performance was evaluated under different conditions, considering components like tanks, pumps, valves, and fuel metering units. The simulation results and power consumption analysis demonstrated the model's effectiveness in assessing various operating conditions and component geometries.

For sustainable aircraft engines, the application of DT focused on fuel systems. A DT model of a fuel cell for a hybrid electric vehicle is proposed by Bartolucci et al. [36]. Their proposed model simulates the dynamic behaviour of hydrogen energy systems and auxiliary systems with high fidelity. They used fuzzy logic controllers to implement energy management strategies and optimized control parameters through genetic algorithms to adapt to different driving conditions. Stoumpos et al. [57] explore the safety issues of marine dual fuel (DF) engines under different operating modes, especially considering the failure or failure of sensors and actuators. The authors used GT-ISE software to construct a DT model of DF engines, which can simulate the engine's response under steady-state and transient conditions. They also used Fault Operation Simulator (FOS) to simulate faults or failures of sensors and actuators. The author used the OREDA database and other databases to obtain the failure rate and failure operation data of engine components. A WEG Digital Twin application composed of motors and controls in the WEGnology Internet of Things (IoT) platform is proposed by Junckes *et al.* [58]. The proposed model provides an increase in energy efficiency and generates insights for the design of new products. Duarte et al. [59] proposed a DT model for predicting pressure in fuel injection systems using machine learning. In their study, the Random Forest algorithm has been used to implement the DT model to predict the pressure level in the fuel injection system. In a different study, Zhu et al. [60] proposed a DT model for vibration monitoring and control in maglev motors.

2.3. Research Gap

In the existing DT technologies, efficient information transfer is incredibly challenging due to resource constraints, random tasks, and resource heterogeneity. In this process, DT technologies should be able to efficiently allocate dispersed resources in the network and reduce energy consumption while improving data processing efficiency [61]. DT technologies can improve efficiency and automate complex engineering assets. However, they require enormous amounts of real-time and historical data for effective simulation and prediction. Aliramezani et al. [62] reviewed the research around the modelling and optimisation of internal combustion engines and highlighted the existing challenges that can be resolved by machine learning techniques, including supervised learning, unsupervised learning, and reinforcement learning. In their study, the identified challenges are real driving emission modelling and control, combustion knocks detection and control, combustion mode transition in multi-mode engines, combustion noise modelling and control, combustion instability and cyclic variability control, costly and time-consuming engine calibration, and fault diagnostics of some ICE components [62]. In the context of an aero-engine, applying the data-driven methods for extracting the relationship between the engine inputs and outputs for direct thrust control is mentioned in [63]. Mouzakitis et al. [64] suggested that AI models with high-performance computing systems can support DT models to run smoothly [64].

Agouzzal and Abbou [65] argued that DT technologies are key for achieving low-cost and sustainable energy transformation, but there are also some technical, standard, and security issues that need to be addressed. Computation of enormous amounts of data with limited resources is a major obstacle to improving the Industrial Internet of Things (IIoT) service level. To reduce the communication overhead between the physical devices and the digital space, a federated learning approach can improve communication efficiency and reduce transmission energy consumption. The combination of the DT model and asynchronous transmission scheme to solve the sub-problems based on the deep neural network model to further decompose the problem is one

of the approaches [66]. Bortolini et al. [67] reviewed the applications of DTs in energy-efficient buildings. They acknowledged the potential of DTs while highlighting challenges in data integration, decision-making, sensor selection and data visualisation. Artificial neural networks (ANN) and hybrid approaches combining white-box and black-box models are commonly used for developing DTs in this context.
The existing literature on DT, system efficiency, and energy consumption in different applications confirms that DT can be a promising technology to monitor and control systems' emissions, energy consumption and efficiency. This paper contributes to the existing literature by expanding the application of DT in the aviation industry and proposing the DT architecture for a sustainable control system of an aircraft.

3. Methodology

The overall research methodology to carry out this work is presented in Figure 3. The proposed methodology includes five main steps: theoretical background, problem statement, DT architecture development, evaluation of the DT architecture and finally, discussion and impact analysis.

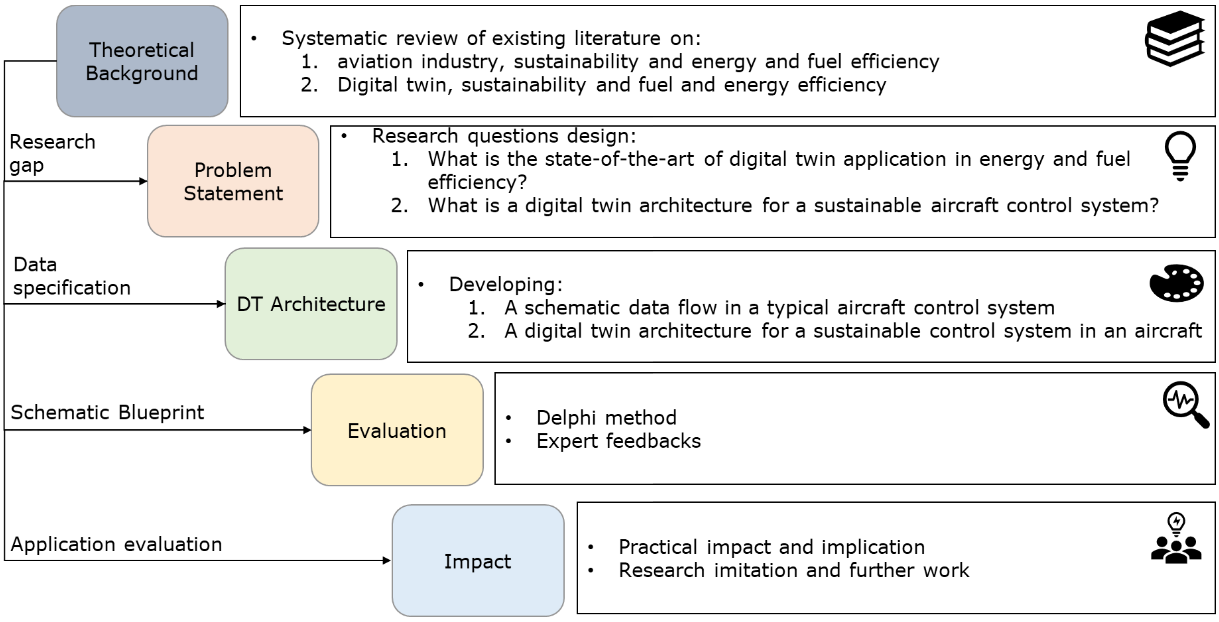


Figure 3. Research Methodology

3.1. Theoretical background

The research work is mainly built on a systematic review of the existing literature in the aviation industry, sustainability, digital twin and energy and fuel efficiency. To establish the state-of-the-art within the scope of the research, a two-folded systematic literature search is carried out. Scopus was used to find the relevant documents. Besides, the existing frameworks, architectures around DT and the relevant Standards are searched through Google Scholar. In the Scopus repository search, no limitations are applied in terms of year, source title, source type, and keywords. However, the documents on healthcare, medicine, agriculture, social science art and humanities are excluded. Moreover, books, notes and abstract reports are also excluded from the document type. Documents in English and Chinese languages are included since some of the co-authors knew the Chinese language. Two sets of keyword strings are used to create the initial database of documents in Scopus.

(1) TITLE-ABS-KEY (aircraft OR aviation OR aerospace OR aeroplane) AND TITLE-ABS-KEY (manufactur*) AND TITLE-ABS-KEY (efficien* OR sustainab* OR resilien* OR productivity OR agil* OR lean) AND TITLE-ABS-KEY (energy OR fuel) AND TITLE-ABS-KEY (engine)

(2) TITLE-ABS-KEY ("digital twin" OR "digital thread" OR "virtual twin" OR "cyber twin" OR "digital replica" OR "cognitive twin" OR "cognitive digital twin" OR "digital data hub" OR "digital

shadow" OR "digital mirror") AND TITLE-ABS-KEY
(efficien* OR sustainab* OR resilien* OR productivity OR agil* OR lean) AND TITLE-ABS-KEY
(fuel OR energy)

The initial search yielded 1363 documents, including 574 and 789 from the first and second keyword strings, respectively. In the documents' screening stage, the title and abstracts of documents were reviewed to shortlist the documents relevant to digital twin applications in the sustainable aviation industry and complex engineering assets. At this stage, duplicates and conference reviews are excluded. Also, the documents on the topics of sustainability in DT, efficiency in building DT, integrated energy systems in housing and construction, and network DT are excluded. This resulted in the exclusion of 939 documents. This left a database comprising 212 articles for full-text screening for eligibility. At this stage, the documents without actual contributions, real DT model development, being related to manufacturing in the aviation industry or high-value assets are excluded. This left a database comprising 75 articles for literature review. The literature search completed is based on PRISMA guidelines, as illustrated in Figure 4.

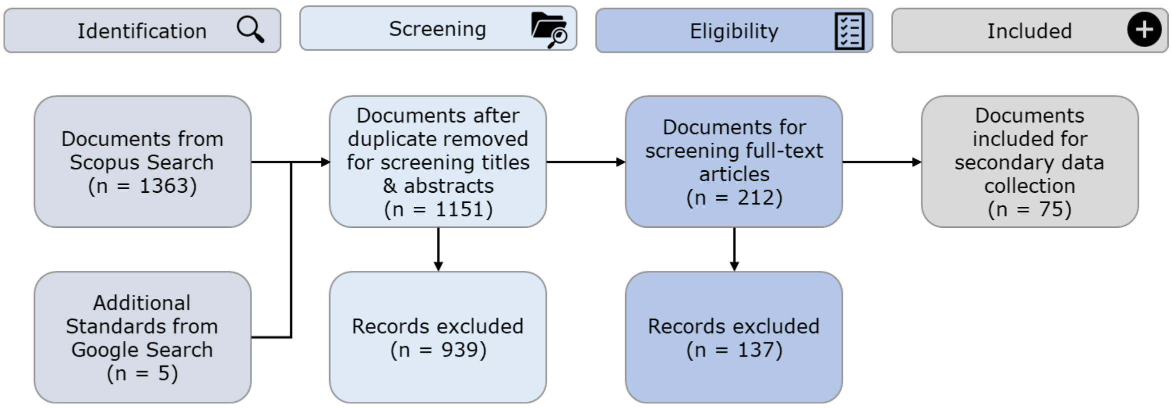


Figure 4. PRISMA flow chart for collection of documents for literature review

3.2. Problem Statement

A thorough literature review is completed to find the answer to the problem of 'How can DT assist with improving engine sustainability and efficiency in the aviation industry?'. To address this, two main search question is designed to understand the state-of-the-art digital twin application in energy and fuel efficiency, and the existing knowledge about digital twin architecture for a sustainable aircraft control system. After completing the literature review, the contribution of this work is drawn towards proposing a DT architecture for a sustainable control system of an aircraft.

3.3. DT Architecture

DT architecture should enable effective data management automation as well as online processing and decision-making. Investigations on multiple software, data platforms, and standards models fuelled the present architecture development. ISO 23247 DT reference architecture depends on the standards and technologies available to model the observable manufacturing elements. Different manufacturing domains can use different data standards. As a framework, this document does not prescribe specific data formats and communication protocols. The scopes of the four parts of this series are (i) ISO 23247-1: General principles and requirements for developing digital twins in manufacturing; (ii) ISO 23247-2: Reference architecture with functional views. (iii) ISO 23247-3: List of basic information attributes for the observable manufacturing elements. (iv) ISO 23247-4: Technical requirements for information exchange between entities within the reference architecture. The developed architecture makes use of the ISO 23247-2 and ISO 23247-4 standards to implement a high-level architecture for the implementation of aircraft engine sustainable control systems.

3.4. Evaluation

Several internal workshops with academic experts in DT, IoT and data architecture are completed to review, enhance, and verify the proposed DT architecture. The final proposed architecture is presented and discussed in an academic panel at the University Research Centre, and the evaluation is completed using the Delphi method.

3.5. Impact

The impact of the application of the proposed DT architecture in a sustainable control system of an aircraft is outlined. This research argued the DT impacts on energy efficiency, fuel consumption, and emission reduction according to the existing knowledge and based on the applicability of the proposed DT architecture across data management, data monitoring, and intelligent and automated decision-making.

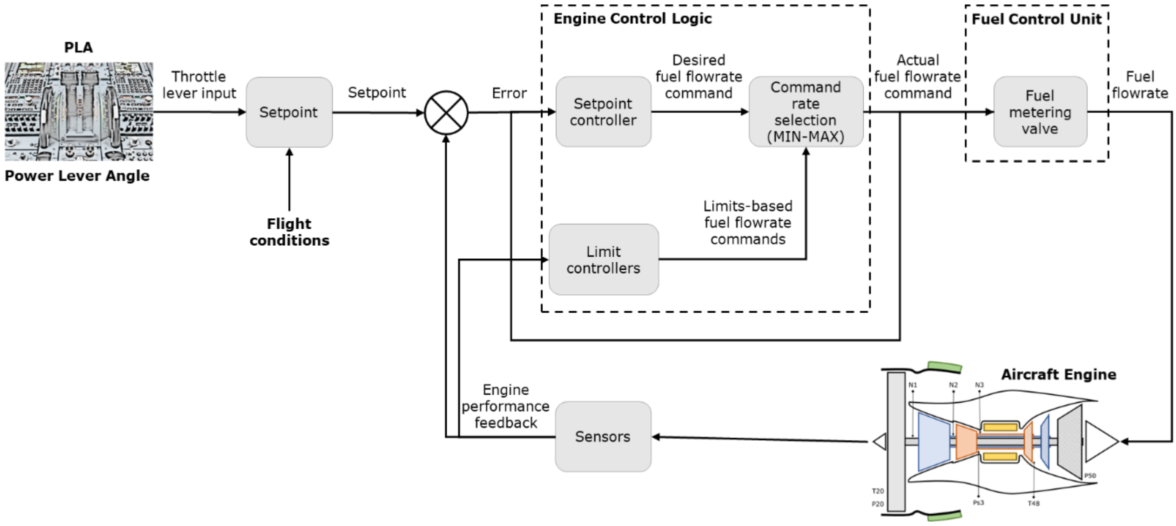
4. Digital Twin Architecture for an Aircraft Engine Sustainable Control System

In this section, a schematic architecture for a typical aircraft engine control system is presented in Figure 5. This architecture provides an overview of how the control system collects and processes the environmental and operational data in the engine to set the specifications that allow the engine to operate efficiently. The proposed Digital Twin architecture of a sustainable control system for aircraft engines is presented in Figure 6. The DT architecture extends the capability of the control system by allowing continuous real-time collection, assessment, analysis, and prediction of the fuel and energy consumption of the aircraft to provide a sustainable and efficient operation.

4.1. Aircraft Engine Control System

Before a flight, the request for a change in thrust is initiated by the pilot through the throttle lever [68], [69]. The Power Lever Angle (PLA) captures the change in the angle of the throttle lever and transmits a reference signal to the engine control unit (ECU). The ECU outputs the actual fuel flowrate command signal to the fuel metering valve actuator, which controls the fuel flow rate to the engine combustor, to achieve the requested change in thrust within the operational and safety limits of the aircraft engine. The fan speed (N1) or engine pressure ratio (EPR) can be used to measure thrust through the engine control system using sensors. N1 is the speed of rotation of the LP shaft, and EPR is the total pressure ratio between the inlet and outlet of the aircraft engine. These parameters are fundamental indicators of engine performance, used to control the engine's thrust output. The mapping of thrust into the equivalent N1 or EPR is performed at the setpoint. The difference between the desired N1 or EPR and the actual N1 or EPR is obtained using the sensor data from the engine performance feedback signal. The difference is defined as an error that the ECU reduces while considering the limits of the aircraft engine. In addition, the flight conditions are considered to account for the variations (e.g., variations in air density affect thrust produced) in environmental conditions that can affect the performance of the aircraft engine.

The ECU has three key components: a setpoint controller, limit controllers, and a command rate selection (MIN-MAX) logic.[70] The setpoint controller works on the error signal to determine the desired fuel flow rate that corresponds to the change in thrust request from the pilot. However, an aircraft engine has some critical operational and safety limits, such as maximum rotor speed, maximum temperature of the turbine, minimum compressor surge margin, maximum static pressure to prevent combustor pressurization and minimum fuel flow to prevent lean blowout.[71] The purpose of the two other components of the ECU is to act as a protection logic that prevents the aircraft engine from exceeding the operational and safety limits. The limit controllers determine the fuel flow rate based on the operating conditions of the aircraft engine obtained from the engine performance feedback signal. These include a combustion blowout regulator that considers Ps3, a fan speed regulator that considers N1 and P20, and structural limit regulators that consider T48, Ps3, N2, and N3. The command rate selection (MIN-MAX) logic compares the limits-based fuel flowrate commands from the limit controllers and the desired fuel flowrate command from the setpoint controller and selects the one (actual fuel flowrate command) that will ensure no limits are exceeded.[70] The actual fuel flow rate command is sent as an actuating signal to the fuel metering unit (FMU) of the fuel control unit (FCU). In the FMU, the fuel metering valve actuator is adjusted to deliver the required fuel flow rate to the combustor of the aircraft engine, where the fuel is burned to drive the turbine and connected compressors. Thrust is thus produced from the resulting airflow through the engine, including both the core and the bypass flow paths.



PLA	Throttle lever angle
Flight conditions	Aircraft altitude LP compressor (fan) inlet temperature (T20) Aircraft Mach number
Setpoint	Desired EPR or N1
Error	Difference between desired EPR or N1 and actual EPR or N1
Limit controllers	Structural limit regulator (T48, Ps3, N2, N3) Combustion blowout regulator (Ps3) Fan speed regulator (N1, P20)
Engine performance feedback	Fan speed (N1) IP shaft speed (N2) HP shaft speed (N3) Engine pressure ratio (EPR) HP compressor exit static pressure (Ps3) HP turbine exit temperature (T48) LP compressor (fan) inlet pressure (P20)

Figure 5. Typical aircraft engine control system

4.2. DT Architecture

The proposed DT architecture is presented in Figure 6. The proposed architecture is developed based on the expert's knowledge of academics in DT as primary data, and following the systematic documents search, review and collecting the secondary data from the existing literature. The proposed DT has physical space, virtual spaces, and an edge layer. The physical space is composed of aircraft engines and users. The virtual space includes IoT device management, resource access and interchange, cognitive module, interface, and cyber security platform. The edge layer interlinks the physical and virtual domains through the interface, measurement value and feedback.

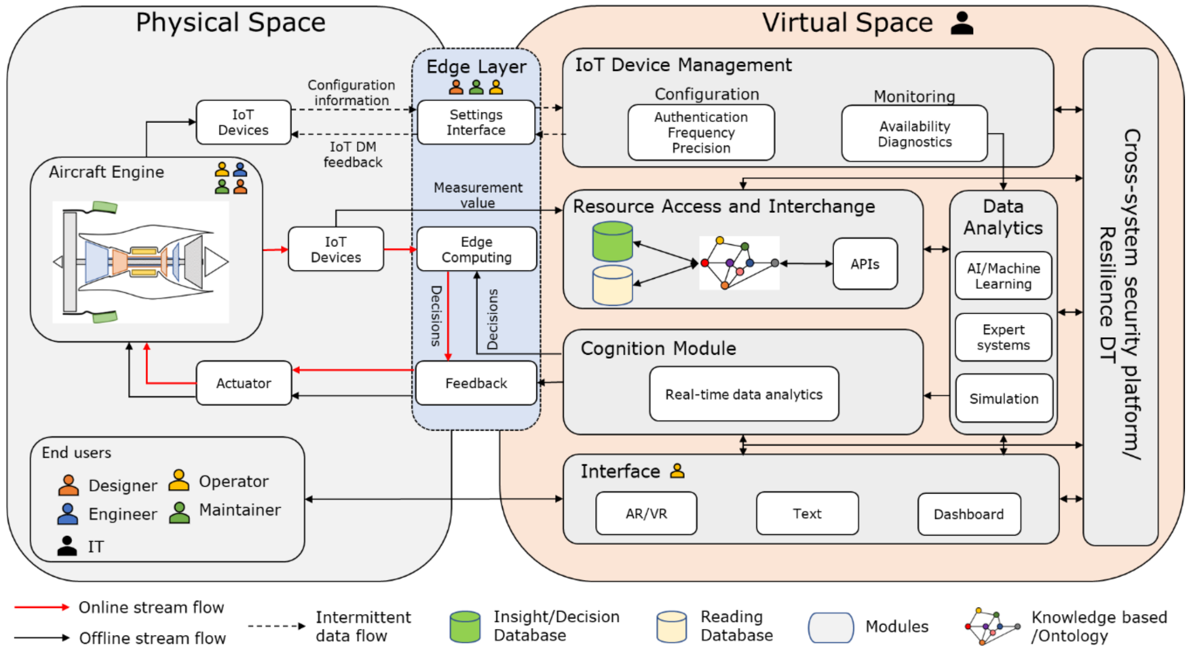


Figure 6. DT Architecture for a Sustainable Aircraft Engine Control System

4.2.1. Physical Space

In the proposed DT architecture, the physical space consists of the aircraft engine equipped with IoT devices and actuators. IoT devices seamlessly collect real-time data from the engine, its control system, and the environment (e.g. sensors measuring rotor speeds, pressure, temperature, etc.). This data is then transmitted to the virtual space through the edge layer, forming the basis for continuous monitoring and analysis. Additionally, the IoT devices enable bi-directional communication with the IoT Device Management (DM) module, allowing intermittent yet seamless data exchange. The setting interface module within the edge layer allows these devices to be configured and managed, ensuring optimal alignment with desired parameters. Moreover, mechanisms are employed to monitor the operation of the IoT devices and address potential failures, ensuring continuous operation. Furthermore, actuators are employed for making responsive adjustments within the engine based on the feedback received from the edge layer. For instance, the fuel metering valve actuator regulates fuel flow rates to prevent sudden thrust fluctuations, ensuring a consistent and steady engine performance. This guides combustion, powering turbines and compressors for the required aircraft thrust, while enhancing aircraft's efficiency and sustainability.

Within the proposed DT architecture of the aircraft engine control system, five user roles contribute to improving the sustainability and efficient operation of aircraft engines. *Designers* employ DT data analytics insights to guide sustainable design decisions by modifying design and/or material parameters, assessing performance under different conditions and identifying areas for improvement. This can enhance system sustainability and efficiency while also establishing a link between data-driven insights and innovative design practices. *Engineers* use DT-driven insights to conduct in-depth performance analyses. By comparing real-world data with the DT's predictions, they can identify deviations, validate models, and improve engines' efficiency and sustainability. Furthermore, *operators* utilise the DT's virtual data from the cognition module for real-time optimisation, monitoring performance metrics, adjusting parameters and promptly responding to anomalies for enhanced sustainability. In parallel, through continuous monitoring and analysis of data from the DT, *maintainers* can predict maintenance needs more accurately. They can anticipate potential issues, plan maintenance schedules, and replace components before they fail, reducing downtime and extending the lifespan of the aircraft engine. Additionally, *IT professionals* enable seamless DT operation through interface design, data security and technology integration, ensuring a seamless connection between the physical and virtual spaces. All users derive valuable insights from the interface module, which enables well-informed decisions through Augmented Reality (AR), Virtual Reality (VR), text-based interactions and visualisations. This collaborative interdisciplinary approach emphasises the significance of expertise across diverse fields and insights driven by users, thus enhancing the engine control system's capacity for efficient and sustainable operation.

4.2.2. Virtual Space

IoT Devise Management: The data collected in the physical space is configured and monitored through the IoT Device Management section in the virtual space, which has two main primary functions: one is to sense the state of the environment by configuring the complex environmental information around it, and the other is to monitor the condition of the physical entity itself. Under the set interface protocol, the IoT device collects data according to the established rules. By selecting different frequencies, the system's accuracy is constantly adjusted to achieve the function of system environment configuration. The data of the physical entity itself will be presented through the availability, and the diagnosis of its state can realise the function of monitoring the aircraft engine.

Resource Access and Interchange: The resource access and Interchange module enables information and knowledge management. Measurements collected in the edge layer are stored, linked, and shared through application programming interfaces (APIs). DT Storage systems should enable high resource availability (fast information storage and retrieval), fault tolerance, and scalability. Three different types of databases are used in this framework—the first type stores data from observable assets or process measurements. The second type of database represents both insights obtained from the analytics and decision systems. The third database is the ontology-based knowledge graph, which enables shared semantics, data linkage, and both user and contextual knowledge storage. The summary of key data, knowledge and insight databases are summarised in Table 1.

Table 1. The summary of identified reading, knowledge, and insight dataset within the proposed DT

Reading Database	Knowledge Database	Insight Database
Flight & Environmental Parameters		
Air humidity (g/m^3) Aircraft altitude (m) Aircraft cruising altitude (m) Aircraft airspeed (mph) Aircraft ground speed (mph) Engine inlet air temperature (°C) Engine revolutions /minute (RPM) Engine running temperature (°C) Engine coolant temperature (°C) Engine oil temperature (°C) HPT rotation speed (RPM) Intake-air temperature (°C) …	Air density (kg/m^3) Air humidity effect (%) Aircraft speed limits (mph) Aircraft ceiling (ft) Aircraft required take-off distance(ft) Aircraft climb rate (ft/min) Aircraft controllability speeds (mph) Optimal engine temperature/limit (°C) RPM error (%)	Aircraft routing Environmental control Flight planning
Engine Specification & Performance Parameters		
Compressor inlet pressure (bar) Compressor discharge pressure (bar) Engine number of cylinders Engine cylinder bore (in) Engine turbocharger (in) Rated power (hp or kW) Engine ignition angle (°) Engine ignition timing (°) Engine stroke cycle Engine vibration (m/s^2) Engine net thrust (kg) Engine oil pressure (bar) Engine inlet air pressure (bar)	Boost pressure error (%) Engine performance trends Engine efficiency level (%) Engine power output (hp or kW) Engine Load (%) Nozzle adjustment Optimal ignition timing (°) Optimal pressure range/limit (bar) RPM limits for different flight RPM trends for health analysis Thermal efficiency level (%) Thermal capacity (J/°C) Thermal stress analysis	Anomaly detection Engine health monitoring Oil system health control Power control system

Engine incoming air velocity (m/s)	Thrust (N)	
Exhaust gas (EWG) velocity (m/s)	Thrust variation	
Exhaust gas response time	Turbine performance	
Gas Valve actuator response time	Velocity limits (m/s)	
Gas/Air Valve response time	Warning thresholds	
Intake variable valve timing		
…		
Emission & Combustion Parameters		
Exhaust gas (EWG) temperature	Air mass flow rate of air (kg/s)	Corrective actions to reduce emissions.
Exhaust variable valve timing	Aircraft fuel efficiency (%)	
EWG recirculation surface tension	CO_2e emission (tonnes)	
	Energy consumption (KWh)	Energy consumption control
Fuel density (kg/m^3)	Energy conservation (KWh)	Energy conservation control
Fuel pressure (bar)	Emission Index (EI)	Energy wastage control
Fuel temperature	Flight trends/profile (optimal)	Energy control system
Fuel response time	Fuel consumption trends	Dual fuel control
Fuel kinematic viscosity (mm^2/s)	Fuel mass flow rate (kg/s)	
Greenhouse Gas Emission (GHG) composition	Fuel manifold pressure error (%)	
	Ignition timing effect on emissions	
	Optimal fuel consumption (kg/kN/h)	
Throttle valve position	SAF blended ratio (%)	
Bleed valve actuator	Soot emissions index	
Stator vane actuator	Waste Heat Recovery	
Clearance control actuator	Active clearance control	
Number of flying hours (h)		
Number of flight cycle		
…		

Cognition module: The cognition module is one of the vital components in the proposed DT system, and its function is to generate an optimal sequence of control signals for action based on the current system state, user inputs and given constraints to achieve expected behaviours. Referring to the definition in [72], the cognition module is a kind of intelligent agent that can perceive its environment and current states, meanwhile taking actions to achieve goals, which is similar to a human's advanced cognition capability, and it is called agent-based method.

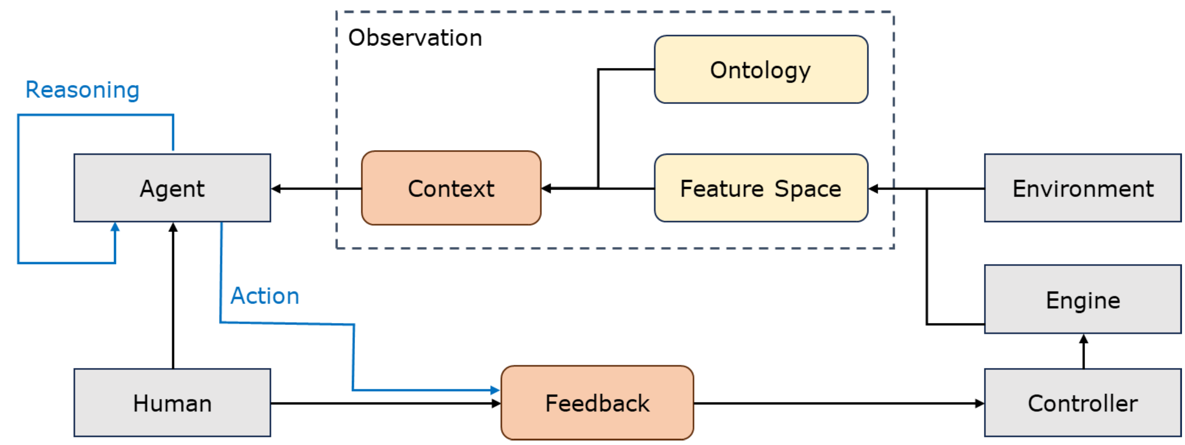


Figure 7. The diagram of the agent-based cognition module

Figure 7 shows how the cognition module works with human beings together to operate the engine. The workflow can be divided into three subtasks listed as follows:

- *Observation*: Characterize the running state of the engine along with the situations of its surroundings.
- *Reasoning*: derive system instructions to guide the system adjustment.

- *Action*: Obtain the controller parameters from reasoning results with user inputs to adapt the adjustment.

The first subtask can be described as a problem of developing context-aware applications, where context is defined as any piece of information used for representing the situation of an entry [73]. The second subtask can be regarded as a decision-making problem, while the final one is about control strategy acquisition. For the context-aware issue in the observation section, the main challenge is constructing mapping between the raw data from sensors on the engine and the domain-specific information, such as concepts of entities and related relationships between these concepts [74]. Thanks to the great leap in machine learning, nonlinear data-driven models like neural networks can be trained for various purposes to elaborate low-level sensory data to abstract feature representation (feature space) [75], enabling the system to perform some advanced tasks such as data clustering, abnormal detection, and fault prediction. Nevertheless, the latent feature space learned by machines, for instance, a high-dimensional vector space [76], cannot be treated as context information modelling because of the lack of common sense and knowledge from human beings, which is difficult to capture from pure data. To address this problem, ontology-based context modelling is proposed to explicitly represent entries and relations among them in a machine-understandable way [77], such as a graph structure format, allowing the machine to do more advanced semantic reasoning [78]. A mixture of ontology-based context modelling and data-driven analysis approach shed light on building a context-aware system, while its implementation and application in the aero industry are still under investigation.

As for the decision-making in the reasoning section, the machine is expected to select an optimal action to step toward the final goal from a provided solution base or even derive one by itself from scratch. For instance, in the aircraft controller diagram, for the sustainable objective, fuel flow is the most critical variable that needs to be optimized in the decision-making process. Therefore, in this case, the decision-making problem can be further narrowed down to how to derive the optimal fuel flow and relevant parameters according to the current context and requirements of human beings. Then, the system can either select a fuel flow according to a hardcore, well-defined rule-base system or it can learn to obtain the rate by learning. From this perspective, the reasoning is coupled with the action section, in which the decision-making is a reasoning process to determine the variant of the fuel flow in a quantitative way, indicating the trend of adjustment (increase or decrease), while the final controller parameters computation is to drive the real system with accurate signals. In the review [32], several promising methods for synthesizing reasoning and action have been introduced, such as reinforcement learning, iterative learning, and event-based learning. By these methods, the agent can learn how to choose a set of parameters based on the environment without hard programming. The result will be sent to the controller as feedback for the engine operations. Besides, it is important to emphasize that during the reasoning and final action process, human-in-the-loop is still required for monitoring, validating, and finally promoting the action to ensure operational safety and reliability. The human factor is a nonignorable consideration for designing a cognition module based on artificial intelligence [79].

Data Analytics: The data analytics module uses the insight gained from the data to determine the performance of the virtual representation of the aircraft engine throughout its lifecycle. The module determines how the aircraft engine can operate efficiently in its current state. Three main modules of analytics are presented in the architecture. The first module, namely AI-Machine Learning, consists of the application of data-driven approaches to achieve the intended DT goal. The second module is the Expert system, where the physical knowledge of the system can be employed. The last module, which is the simulation, can enable future health management prognosis and “what if” type of scenario optimisation of the DT. These modules enable offline learning (model training) as well as offline and near-time analytics. The learned model can then be employed in the cognition module for real-time analysis.

During flight operations, the carbon emission from an aircraft engine cannot be directly measured. It can only be inferred from measured or controlled variables [80]. The fuel metering unit in the fuel control system of an aircraft supplies fuel through the fuel nozzle to the combustor based on the pilot’s thrust demand, including any safety limits, and on the mass of compressed air flowing through the combustor [81]. This allows the assumption that the combustion of jet fuel is a stoichiometric chemical reaction. Consequently, the mass of $CO2$ emitted can be directly linked to the amount of fuel burnt based on the chemical composition of the fuel used [80]. Hence, the carbon emission from an aircraft engine during flight operations can be calculated using fuel use data. The approach recommended by the ICAO (International Civil Aviation Organisation) and adopted by airline operators in the aerospace industry aligns with the monitoring, reporting and verification requirements of the CORSIA (Carbon Offsetting and Reduction Scheme for International Aviation), which is a voluntary carbon offset and emission reduction scheme that has been applied to international aviation since 2019. The approach suggests the use of an emission factor and quantified data related to the activity associated with the release of the pollutant. The activity data considered is the amount of fuel consumed per flying hour over a forecasted period. The mapping of this activity data into carbon emissions is performed using a fuel conversion factor (FCF). The generic formula for carbon emission quantification during flight operations is shown in Equation 1.

$$Emissions\ [kgCO_2e] = Fuel\ flowrate\ \left[\frac{kg}{h}\right] \times Flying\ hours\ [h] \times FCF\ \left[\frac{kgCO_2e}{kg}\right] \quad (1)$$

Currently, the fuel flow rate used is a fleet-averaged value over a forecasted period for each engine type over the take-off, cruising, and landing phases. As for the FCF, it is a constant parameter that depends on the type of fuel used, and what part of the value chain is being considered by the stakeholder - Tank-to-Wake (TTW) or Well-to-Wake (WTW) [75] [82]. For example, consider the emissions resulting from the combustion of Jet-A fuel during flight operations; using the ICAO guidelines, the TTW FCF is 3.16 kgCO2/kg fuel while WTW FCF is about 3.88 kgCO2e/kg fuel. TTW FCF calculates the amount of CO2 emitted downstream based on the stoichiometric chemical reaction of 1 kg of jet fuel. On the other hand, WTW FCF accounts for both the upstream and downstream greenhouse gas emissions based on the life cycle emission value of jet fuel. The engine control system works with the fuel control system to determine and supply the required fuel flow rate to the combustor. Consequently, the decision-making efficiency and effectiveness of these systems have a direct impact on carbon emissions.

Interface: The Interface Module holds a significant role within our digital twin architecture developed for aircraft engines. By integrating Augmented Reality/Virtual Reality (AR/VR), text-based interactions, and a dashboard, this module facilitates human-machine interaction, connecting the digital twin system with human users such as engineers, maintenance workers, and operators. To enable seamless interaction between these two parties, the module is designed to fulfil two primary functions. Firstly, it visually communicates real-time operating data from the engine system and other modules within the digital twin, providing users with a clear understanding of the current situation. Secondly, it translates user commands into machine language, thereby controlling the digital twin's operations, and subsequently feeds back operation outcomes to the physical engine system. This interface module delineates how human users engage within this digital twin system. Based on the power of AR/VR, the Interface Module offers an immersive experience, enabling engineers and operators to engage with virtual replicas of the engine components, visualize intricate processes, and conduct real-time assessments; this interaction facilitates maintenance simulations and diagnostic evaluations.

The Text component of the Interface Module establishes a bridge between human and machine data, engineers can communicate seamlessly with the engine's digital twin, extracting critical insights, querying performance parameters, and receiving a concise yet comprehensive response with a user-friendly interface. This communication empowers engineers to quickly understand the operation of the engine and respond promptly to complex problems, thereby reducing operational downtime. The Dashboard provides a consolidated overview of the engine's operational status, performance metrics, and predictive analytics as a supplement to these immersive textual elements. This real-time visualization empowers operators and engineers with actionable information, facilitating resource allocation and adaptive maintenance practices.

Cyber Security and Resilience: The cross-system security platform/ resilience DT component is a module that communicates with all the modules in the virtual space. In the digital twin system, the data collected in the physical space is transferred to the virtual space for a series of management and analysis, and then feedback to the physical space; the entire process is like an ever-refined circle. During this process, the communication between all modules involves security issues. Therefore, this module is existence ensures that the system operates smoothly in a safe state. Similarly, the resilience proposed in this architecture refers to the fact that the digital twin, its own system, is resilient. In the digital twin system, the virtual space is a real-time representation of the physical space, but the physical space and the virtual space cannot be kept 100% the same; with the change of time, with the update of data iteration, this part of the design is to ensure that the virtual space in a specific range of deviation from the physical space to form an accurate description.

4.2.3. Edge Layer

In the proposed DT architecture, the 'Edge Layer' provides the infrastructure that links the physical space to the virtual space and an edge computing module that allows Real-time analytic with offline build analytics in the data analytic layer. The edge layer allows data collection and data transmission from physical to virtual space, and real-time feedback from processed data within the virtual space to the physical space. Data collection occurs through IoT devices, sensors, cameras, and other data sources in the physical space about the engine and relevant processes, which are monitors for energy efficiency, and transmitted to the 'IoT devise management' module. In some cases, some data measures are directly collected and locally analysed by the IoT devices at the edge layer (edge computing module) and then transmitted to the 'feedback' module within the virtual space. Finally, the edge layer also enables real-time feedback from the 'cognition module' to the physical space using the feedback module and several actuators. This automated feedback allows some of the decision-making and actions within the engine without relying on the 'interface' module and interactions from 'end-users'.

5. Discussion

This study highlights that integrating Digital Twin (DT) technology with aircraft engines is a pivotal advancement for the sustainable aviation industry. This research work contributed to the body of knowledge by presenting a DT architecture designed to address the challenge of data availability and inadequate data quality in aircraft engine control systems, with the aim of enhancing engine sustainability and efficiency. The importance of DT applications for sustainable systems and energy efficiency is highlighted in several studies [11], [13], [38]. However, the implementation of DT for energy and fuel efficiency in aircraft engines is limited and has not been discussed thoroughly in the literature. Nevertheless, the impact of DT on energy consumption and CO_2e footprint reduction in complex engineering assets is evident [13]. Moreover, the capability of DT regarding real-time monitoring, proactive anomaly detection, forecasting and automating feedback allows intelligent and effective decision-making within automated energy control systems, in which the literature refers to such DT as a solution for Energy IoT (EIoT) [20]. The integration of DT technology with the energy management systems and as part of the decision support systems can improve the energy distribution, optimisation and, therefore, performance of the asset [23], [44].

This study considered the Ardebili et al. [20] observation and presented a DT-enabled control system for the thrust control of an aircraft engine. This study focuses on the engine control system to demonstrate the DT integration and its application for delivering sustainable aviation. A typical control system, including the fuel system, is demonstrated in Figure 5. The integrated system determines and supplies the required fuel flow rate to the combustor. Consequently, the decision-making efficiency and effectiveness of these systems and their ability to account for changes in operation and environmental conditions have a direct impact on the sustainability indicator. The fuel flow rate is the critical indicator to assess CO_2e emissions and sustainability during the flight operation (see Equation 1). In aircraft engines, the fuel flow rate to achieve a desired engine pressure ratio (EPR) or fan speed (N1) is not only dependent on the pilot command, and operational and safety limits but also on the changes in operational and environmental conditions of the engine. During flight operations, the components of the aircraft engine degrade. This can take the form of hardware ageing deterioration, and contamination by airborne particles. The result is an increased Specific Fuel Consumption (SFC) to achieve the desired thrust [68], [69]. The proposed DT for the control system makes it self-aware of the engine's current state and gives the control system the ability to adapt to changes in operational and environmental conditions dynamically with a view to optimising energy efficiency and fuel consumption. As a result, the aircraft engine does not operate in a conservative manner; it will have a sustainable and efficient operation based on the extended capability of the DT-enabled control system, which allows continuous real-time collection, assessment, analysis, and prediction of fuel and energy consumption.

The integration of DT principles in the optimisation of engine sustainability-related parameters aligns with the aviation industry's drive for improved energy efficiency and environmentally conscious propulsion systems. The literature highlights the effectiveness of the DT-driven optimisation approach in refining operations [36], [41], [44], [45]. By incorporating real-time data into the DT model and integrating feedback into key performance indicators, this approach facilitates iterative optimisation adjustments and enhances energy efficiency strategies. These studies collectively emphasise DT's potential to refine engine operation, conserve energy and optimise system efficiency. In addition, the DT system enables real-time data using embedded IoT devices and empowers precise monitoring and analysis of engine parameters and provides a comprehensive sustainability assessment of engine behaviour across diverse conditions. This data-driven approach facilitates the refinement of parameters for optimal performance. Additionally, the dynamic feedback loop between physical and virtual spaces, facilitated by DT, ensures continuous parameter monitoring and adjustment. This equips engineers to not only enhance real-time performance but also adapt to evolving operational demands. As a result, DT goes beyond traditional static models by introducing dynamic, data-informed approaches, offering significant improvements in aircraft engine operational efficiency, reliability, and sustainability.

Recent studies highlight a growing interest in integrating semantic technologies with DTs, particularly the association of ontology and DTs. Boschert et al. [83] referred to the next-gen Digital Twin, known as nexus, as one that fosters system interconnectivity through semantic tools, such as ontologies. Akroyd et al. [83] proposed the idea of the Universal Digital Twin, a DT that employs a dynamic knowledge graph to enhance cross-domain interoperability. Lu et al. [83] introduced the idea of the Cognitive Twin (CT), which is a DT fortified with enriched semantic abilities to aid IoT systems or decision-making processes in manufacturing [84]. Li et al. [85] applied the cognitive twin framework to facilitate the co-simulation of intricate engineering assets, integrating multiple digital tools. Abburu et al. [86] developed the COGNITWIN software toolkit tailored for the process industry, viewing the CT as an advanced form of the Hybrid DT (HT). The latter was seen as an advancement of the conventional DT. Combining ontology concepts with digital twins improves interoperability and integration with physical systems and equipment [87]. The emergence of AI technology has significantly influenced the evolution of DT technologies primarily due to two pivotal factors. Firstly, its ability to extract insightful information from vast and intricate non-linear datasets enables an efficient recognition and analysis of system states. Secondly, the integration of decision-making processes through algorithms like fuzzy logic, bio-inspired algorithms, and reinforcement learning allows for automated decision support, which can be coupled with the controller for system operation [49]. Although intelligent engine with relevant digital technology such as IoT, artificial intelligence and knowledge engineering is now an active research topic, the business benefits should also be simultaneously considered when introducing the above technologies into the current engine lifecycle to avoid a technique-sage development [74], which is a less investigated topic.

6. Conclusion

In the aviation industry, there are several approaches to improve sustainability, such as flight efficiency improvement, sustainable aviation fuel (SAF), renewable and mixed energies, and decarbonisation, as illustrated in Figure 1. This paper focuses on the application of some emerging technologies such as digital twin (DT), artificial intelligence (AI) and ontologies, to enhance fuel and energy efficiency within an aircraft engine. A thorough systematic literature review (see Figure 4) is conducted to identify the research contribution, gaps, and data specification for this research. A DT architecture for a sustainable control system of an aircraft is proposed in this paper (see Figure 6). The typical functional flow diagram of an engine control system is presented in Figure 5. The DT architecture is developed based on a thorough literature review around sustainability and digital twin, and elicitation of expert knowledge using the Delphi method. The architecture follows the existing guidelines and standards in ISO 23247-1:2021. It is argued that the proposed DT architecture enhances energy efficiency, fuel consumption, and environmentally sustainable operation of an aircraft. The DT architecture enables (near) real-time data collection, monitoring, and analysis from the physical space – including aircraft engine and operator – and optimises and feedback the insights to the end users, including, designers, engineers, operators, and maintainers. The DT system is composed of physical aircraft, end users, IoT devices, actuators, and the edge layer that integrates with the virtual space, including IoT devise management, resource access and interchange, data analytics, cognition module, interface, and the cross-system securing platform. The proposed DT architecture considered several modules within the virtual space to enable intelligent data management, analysis, and feedback with a view to enhancing energy efficiency, fuel efficiency and environmental sustainability. The resource access and interchange module proposed an integrated API that connects with an insight and decision database, a reading database, and an ontology-based knowledge base. The list of key databases is summarised in Table 1.

Further studies should explore the ontology technologies for the DT knowledge base development and implementation. Ontologies are formal representations of knowledge that define concepts and relationships within a domain. Combining these two concepts can offer several benefits in creating and managing Digital Twins, such as semantic interoperability, data integration, modelling complex systems, knowledge sharing and reuse, reasoning and inference, adaptability, lifecycle management and collaboration. To implement an ontology-based approach for developing a DT technology, you would typically define the ontology that describes the concepts, properties, and relationships relevant to the physical entity or system. This ontology would serve as the basis for creating digital models, simulations, and data integration processes. Different tools and technologies exist for building and managing ontologies, such as the Web Ontology Language (OWL) and ontology development platforms.

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