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Aircraft Digital Twin Ecosystems for Lifecycle Planning and Management in Sustainable Aviation Transport Systems

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Abstract

Aircraft digital twins are increasingly used for diagnostics, prognostics, and predictive maintenance, but their role as lifecycle-oriented, multi-stakeholder decision-support ecosystems remains insufficiently developed. This paper addresses this gap by proposing a conceptual systems-engineering framework for an aircraft digital twin ecosystem supporting sustainable aviation transport management. The framework integrates physics-based, data-driven, hybrid, probabilistic, and federated modelling approaches and includes a three-layer ecosystem model, formal mathematical representation of aircraft and digital twin lifecycle evolution, federated model updating, lifecycle decision-support scenarios, reference architecture, validation and trustworthiness principles, and a five-level maturity model. Representative aviation industrial cases are used to interpret the framework. The analysis shows that current industrial practice already contains elements of predictive maintenance, fleet analytics, engine health monitoring, and cloud-enabled MRO optimization, but full aircraft-level lifecycle governance, sustainability trade-off analysis, federated validation, and multi-stakeholder decision orchestration remain underdeveloped. The proposed framework positions aircraft digital twins as asset-level instruments for lifecycle planning, coordinated governance, and sustainability-oriented decision support.

Keywords: aircraft digital twin; aircraft lifecycle management; sustainable aviation; predictive maintenance; federated learning; multi-stakeholder ecosystem; systems engineering; sustainable transport systems

1. Introduction

1.1. Background and Motivation

The aviation sector is undergoing a profound transformation driven by increasing system complexity, stringent safety and regulatory requirements, sustainability objectives, and growing pressure to improve lifecycle cost efficiency [1–3]. Modern aircraft operate within highly interconnected technical and organizational environments where operational performance, maintenance strategies, environmental impact, and economic outcomes are closely interdependent [4,5]. Traditional approaches based primarily on static engineering models, scheduled maintenance intervals, and fragmented operational data are increasingly insufficient for supporting lifecycle-oriented planning and management [6,7].

Digital twin (DT) technology has emerged as a key enabler for addressing these challenges. Initially developed in the context of product lifecycle management and complex engineering systems, digital twins provide dynamic virtual representations of physical assets that are continuously updated using data from their real-world counterparts [8–11]. In aviation, where assets are safety-critical, capital-intensive, and highly regulated, digital

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twins are particularly relevant for predictive maintenance, condition-based monitoring, fleet management, performance optimization, and lifecycle decision-making [12–14]. Aircraft generate large volumes of operational, maintenance, environmental, and configuration data, which can be used to update digital representations and improve the quality of planning and management decisions [13,14]. At the same time, the growing importance of sustainability in aviation requires decision-support tools that can integrate safety, reliability, cost, availability, fuel efficiency, emissions, and lifecycle resource use into a coherent analytical framework [2,3,15].

Despite significant progress, many existing digital twin implementations remain fragmented, focusing on isolated components, specific subsystems, or individual lifecycle phases rather than on integrated asset-level ecosystems capable of supporting coordinated planning across stakeholders [6,13,14]. This limits the potential of digital twins to act as system-level instruments for sustainable transport planning and governance.

1.2. Aircraft as the Core Asset of Transport Systems

Rather than addressing aviation as a whole, which represents a highly complex and loosely bounded socio-technical system, this study adopts an asset-centric perspective and focuses on the aircraft as the primary operational unit of the aviation transport system. This choice is methodologically important because the aircraft constitutes a well-defined system-of-interest with clear physical boundaries, measurable performance characteristics, regulated configuration states, and a structured lifecycle from design and manufacturing to operation, maintenance, modernization, and end-of-life management [5,6,16,17].

From a systems-engineering perspective, defining the system-of-interest is a prerequisite for rigorous modelling, architecture development, verification, validation, and lifecycle management [16,17]. The aircraft is not merely one element among many in the aviation system; it is the central technical asset around which multiple planning and management processes are organized. Airlines plan fleet utilization and route assignment around aircraft availability and performance; maintenance, repair, and overhaul organizations manage inspection and repair activities based on aircraft condition; manufacturers and original equipment manufacturers use operational feedback to improve design and reliability; regulators supervise airworthiness and compliance; and airports and air traffic management actors coordinate services around aircraft movement and operational status [5,6,13,14].

This asset-centric perspective provides a tractable analytical level between narrow component-level modelling and broad aviation system-level analysis. Component-level digital twins, such as those developed for engines, landing gear, structural elements, or onboard systems, provide important diagnostic and prognostic capabilities, but they do not by themselves support lifecycle planning at the level of the aircraft as an integrated operational asset [12–14]. Conversely, modelling the aviation system as a whole may obscure the technical and lifecycle mechanisms through which digital twins generate actionable value. The aircraft digital twin therefore offers an appropriate intermediate level for connecting engineering models, operational data, stakeholder-specific decision views, and sustainable transport management objectives [6,14].

By focusing on the aircraft digital twin ecosystem, this paper links detailed asset-level data and models with higher-level planning and management functions. This enables the aircraft to be interpreted not only as a physical object, but also as a lifecycle information system, a decision-support platform, and a core building block of sustainable aviation transport systems [6,13,14].

1.3. Related Works

Aircraft digital twin research has developed rapidly in recent years, particularly in relation to safety-critical components, propulsion systems, structural health monitoring, onboard subsystems, and maintenance-oriented decision support. While general digital twin concepts and enabling technologies have been extensively discussed in the broader engineering literature [8–12], aviation-specific research has mainly focused on diagnostic, prognostic, and operational applications at the level of individual components or subsystems [13,14].

A substantial group of studies addresses aeroengine diagnostics and prognostics. Fentaye et al. [18] proposed a gas-path diagnostic method combining support vector machines and artificial neural networks. Lu et al. [19] applied Dempster–Shafer evidence theory and data fusion for fault diagnosis. Xiong et al. [20] introduced a digital twin framework integrating operational data with long short-term memory models to support engine maintenance decisions. Similarly, Zhou et al. [21] combined Kalman filtering, long short-term memory (LSTM) models, and convolutional neural networks for engine health assessment, Yanhua et al. [22] developed an adaptive correction method for turbofan engines based on LSTM and hybrid optimization, while Li et al. [23] discussed the application of the lifecycle of aeroengine mainshaft bearing based on digital twins.

Other studies have emphasized hybrid digital twin modelling, where physics-based mechanisms are combined with data-driven approaches. The framework proposed in [24] integrates mechanism models and data-driven models for twin-spool turbofan engines. Zaccaria et al. [25] developed a monitoring, diagnostics, and health-management framework for aircraft fleets based on fault signatures, while Yang et al. [26] focused on crack detection in turbofan discs using dynamic equations and vibration-response analysis. Wang et al. [27] addressed life prediction for aircraft structures by combining heterogeneous data sources with finite-element-based digital twin modelling.

Digital twin approaches have also been applied to aircraft subsystems beyond propulsion and structures. Chowdhury et al. [28] presented a model-based solution for an aircraft environmental control system tested on a real aircraft. Ezhilarasu et al. [29] investigated health monitoring of the aircraft electrical power system, integrating simulation models with artificial neural networks for fault isolation and root-cause prediction. The same research stream later introduced the FAVER framework for identifying, isolating, and predicting faults across interacting aircraft subsystems [30,31]. Ramesh et al. [32] explored landing-gear fault simulation using an electric braking system model and recurrent neural networks.

Several contributions have further advanced the integration of physics-based modelling, data fusion, and machine learning for aviation digital twins. Huang et al. [33] proposed an improved digital twin for real-time aeroengine fault detection using degradation-adaptive correction models. Alvarez et al. [34] addressed aircraft airspeed estimation under pitot-tube sensor failure using physics-based simulation and data-fusion techniques. Peng et al. [35] validated an aeroengine digital twin approach through practical testing in an experimental facility.

In parallel with academic research, major aviation industry actors have developed digital platforms that approximate or support aircraft digital twin capabilities. Examples include AVIATAR by Lufthansa Technik [36], Skywise Core by Airbus [37], GE Aerospace Maintenance Insight [38], and Rolls-Royce digital twin and intelligent engine applications [39,40]. These platforms demonstrate the practical relevance of data-driven monitoring, predictive maintenance, fleet-level analytics, and cloud-enabled engine lifecycle management. Their relevance is also discussed in conference and research publications addressing AVIATAR-based predictive health analytics [41,42], Skywise as a big-data platform for predictive and health monitoring [43], and aviation digital twin architectures for cross-stakeholder data management [44].

Bastard et al. [45] described the architecture of the Engine Health Management system developed by Safran Aircraft Engines for the Silvercrest turbofan, covering the full processing chain from airborne data acquisition through state detection, prognostics and advisory generation toward an integrated vehicle health management environment. In 2024, CFM International extended this capability by introducing machine learning-based probabilistic diagnostic and prognostic tools to the monitoring system [46]. Collins Aerospace has developed the Ascentia platform covering hydraulic, pneumatic, electrical power, and landing system analytics across multiple aircraft types [47] and, in 2025, joined the Airbus Digital Alliance for Aviation to integrate Ascentia with the Skywise environment [48]. Research project PASSME addressed airport management [49], and the project CleanSky2 Large Passenger Aircraft sub-programme addressed aerostructural technology development with digital twin elements limited to component-level structural health monitoring [50].

However, both industrial practice and academic discussions indicate that such platforms are often constrained by stakeholder boundaries, proprietary data environments, centralized data ownership, and limited cross-organizational interoperability.

1.4. Research Gap, Contributions and Paper Structure

The literature reviewed above confirms that digital twin research in aviation has advanced significantly in relation to aeroengine diagnostics, structural health monitoring, subsystem-level fault detection, predictive maintenance, and fleet analytics.

However, three important research gaps remain insufficiently addressed.

First, most aircraft digital twin studies and applications remain concentrated at the component, subsystem, or specific operational-function level. They provide strong diagnostic or prognostic capabilities, but they do not fully conceptualize the aircraft digital twin as an integrated lifecycle-oriented ecosystem supporting planning and management decisions across design, manufacturing, operation, MRO, modernization, and end-of-life phases.

Second, existing approaches often treat digital twin outputs as technical indicators rather than as structured stakeholder-specific decision views. This limits their ability to support coordinated decisions among airlines, MRO providers, OEMs, regulators, airports, and service partners.

Third, the governance dimension of aircraft digital twin ecosystems remains underdeveloped. In aviation, data are distributed, proprietary, safety-critical, and regulated; therefore, centralized data integration is often unrealistic. This creates a need for federated learning, controlled model updating, validation gates, access-control mechanisms, auditability, and lifecycle governance structures.

A fourth gap concerns the connection between aircraft digital twins and sustainable transport-system management. In the context of this study, sustainability is defined as the capacity of aircraft lifecycle management decisions to simultaneously reduce operational emissions and fuel consumption, extend productive component life through condition-aware maintenance, minimize material waste across MRO cycles, and preserve residual asset value—thereby connecting asset-level technical outcomes with fleet-level and transport-system-level environmental and resource efficiency objectives. While predictive maintenance and performance monitoring have clear operational value, their contribution to sustainability in this sense is often treated indirectly. While predictive maintenance and performance monitoring have clear operational value, their contribution to sustainability is often treated indirectly. There is still a need for a framework that explicitly connects aircraft technical condition, lifecycle degradation, maintenance actions, fuel efficiency, emissions, resource use, residual value, and end-of-life decisions within a coherent planning and management logic. This is especially important because sustainability in aviation cannot be achieved only through isolated technical optimization; it requires coordinated lifecycle decisions at the asset, fleet, and transport-system levels.

To address these gaps, this paper proposes a lifecycle-oriented aircraft digital twin ecosystem framework for sustainable aviation transport systems. The main contributions of the paper are as follows:

- The paper conceptualizes the aircraft digital twin not only as a virtual representation of a physical aircraft, but as an asset-level lifecycle information, modelling, and decision-support ecosystem connecting technical models, lifecycle data, stakeholder views, and planning outputs.
- The paper develops a formal mathematical structure for representing the aircraft, its digital twin, lifecycle-phase transitions, physics-based models, data-driven models, hybrid models, decision outputs, maintenance optimization, operational optimization, and sustainability-oriented objective functions.
- The paper introduces federated learning and governance mechanisms as first-class architectural elements of aircraft digital twin ecosystems, addressing the practical constraints of distributed aviation data, stakeholder-specific access, validation of local model updates, and auditability of shared model evolution.
- The paper develops a set of decision-support scenarios and a reference architecture comprising data acquisition, model orchestration, decision-support, and stakeholder interface layers, supported by multi-stakeholder connectivity and continuous feedback.
- The paper formulates verification and validation principles for physics-based, AI/ML, software, system-integration, and federated learning components; proposes a five-level maturity model for aircraft digital twin ecosystem adoption; and maps the proposed framework to representative industrial cases.

The paper is organized as follows. Section 2 describes the conceptual systems-engineering research design, including the analytical basis, framework-development logic, and industrial case-mapping method. Section 3 presents the main results of the study, including the proposed aircraft digital twin ecosystem model, its formal representation, decision-support logic, reference architecture, validation principles, and adoption maturity pathway. Section 4 discusses the implications of the framework for sustainable aviation transport systems, maps representative industrial applications to the proposed framework, and identifies limitations and future research directions. Section 5 summarizes the main conclusions and contributions of the study.

2. Materials and Methods

This study adopts a conceptual systems-engineering research design aimed at developing a lifecycle-oriented aircraft digital twin ecosystem framework. The study does not report laboratory experiments or statistical analysis of an operational dataset; instead, it develops an integrative framework by synthesizing concepts from digital twin theory, aircraft lifecycle management, systems engineering, predictive maintenance, stakeholder-oriented decision support, and sustainable transport planning.

The study is based on three methodological assumptions. First, an aircraft digital twin is treated not only as a virtual representation of a physical aircraft, but also as a lifecycle information and decision-support system. Second, aircraft lifecycle management requires the integration of heterogeneous modelling approaches, including physics-based, data-driven, hybrid, probabilistic, and federated models. Third, the value of an aircraft digital twin ecosystem depends on its ability to transform model outputs into planning and management decisions related to maintenance, operations, fleet utilization, compliance, lifecycle governance, and sustainability trade-offs.

Accordingly, the expected outputs of the study are framework-development results: a lifecycle-oriented aircraft digital twin ecosystem model, a formal modelling framework, decision-support scenarios, a reference architecture, a maturity and adoption logic, validation and trustworthiness principles, and an interpretive mapping of representative industrial applications.

The analytical basis comprises four categories of source material: (1) academic literature on digital twins and aircraft lifecycle management; (2) systems-engineering concepts for boundary definition, lifecycle decomposition, and stakeholder modelling; (3) formal modelling constructs developed in the paper; and (4) representative industrial cases used as interpretive reference points. Source material was analyzed across four dimensions: lifecycle coverage, modelling scope, decision-support function, and stakeholder integration.

The framework development followed a four-stage structured synthesis: classification of concepts by lifecycle phase, model type, stakeholder role, and decision function; conceptual synthesis; formalization using mathematical constructs; and interpretive structuring into decision-support scenarios, reference architecture, maturity levels, and industrial case mappings.

To strengthen the internal consistency of this synthesis, a construct traceability check was applied. The principal constructs introduced in the formal framework were traced back to their conceptual origins in the reviewed literature and forward to their corresponding decision-support outputs. This check ensured that the classification stage, conceptual synthesis, mathematical formalization, and interpretive structuring remained aligned. In particular, lifecycle phases, model families, stakeholder views, federated updating, governance rules, and sustainability objectives were retained only when they could be linked both to an identifiable source concept and to a planning, management, or governance function of the proposed aircraft digital twin ecosystem. The detailed traceability matrix is provided in Appendix A. Appendix A provides supporting construct-level traceability between the literature review, conceptual framework, formal constructs, and decision-support outputs. It is retained as an appendix to avoid overloading the main text while documenting the internal consistency of the proposed framework.

Industrial case mapping was used as an interpretive method to relate the proposed aircraft digital twin ecosystem framework to existing aviation digitalization practice. The purpose of this step was not to validate the framework experimentally, but to examine whether its main components can be identified in representative industrial platforms and digital twin-related applications.

Four industrial cases were selected for mapping: Lufthansa Technik's AVIATAR platform [36,41,42], Airbus Skywise [37,43], GE Aerospace Maintenance Insight solutions [38], and Rolls-Royce digital twin and Intelligent Engine applications [39,40]. These cases were selected because they represent different industrial trajectories in aviation digital twin development: predictive maintenance and technical operations platforms, fleet-level data and analytics environments, aircraft and component degradation monitoring, and engine-level digital twins supporting maintenance, efficiency, and lifecycle extension. The cases were selected not for exhaustive market coverage, but for analytical diversity and relevance to the framework dimensions.

The mapping was conducted according to three criteria:

- The dominant digital twin-related function of each case, such as predictive maintenance, fleet analytics, degradation monitoring, or engine lifecycle intelligence.
- The corresponding framework component, including lifecycle modelling, hybrid analytics, stakeholder-specific views, maintenance planning, operational optimization, or lifecycle governance.

- The decision-support output, such as inspection planning, replacement recommendations, fleet performance indicators, early degradation detection, maintenance workscoping, or efficiency-oriented operational recommendations.

The mapping is used as an analytical bridge between the proposed conceptual framework and current industrial practice, rather than as evidence of full operational validation.

3. Results

3.1. The Aircraft Digital Twin Ecosystem Model

The lifecycle of an aircraft and the lifecycle of its digital twin are closely interconnected, evolving in parallel through continuous data exchange, model refinement, and decision feedback. The aircraft progresses through the main phases: design, manufacturing, operation, including maintenance/repair/overhaul (MRO) and modernization, and end-of-life. The digital twin evolves from an initial engineering model to a continuously updated operational and decision-support system (Figure 1).

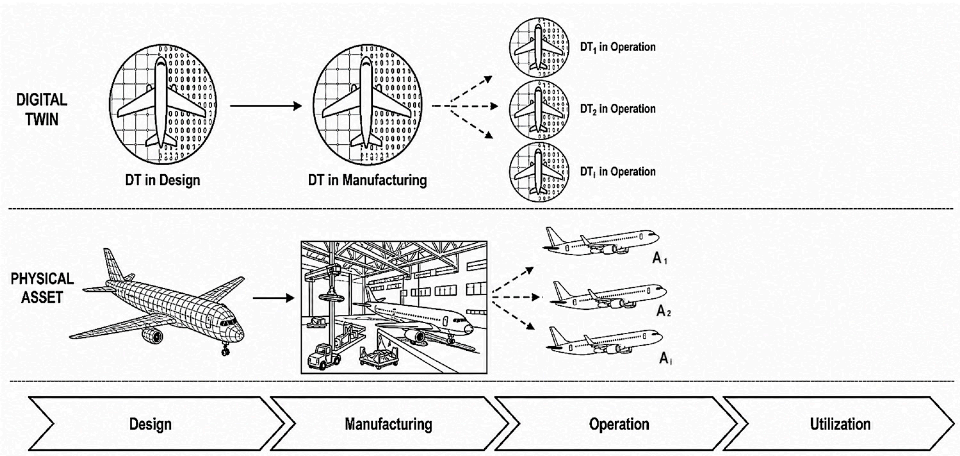

Figure 1. Lifecycle co-evolution of the aircraft and its digital twin across design, manufacturing, operation, maintenance, modernization, and end-of-life phases.

During the design phase, the DT is a virtual engineering construct incorporating design specifications, aerodynamic and structural models, and certification requirements. During manufacturing, it is updated to reflect the as-built configuration, integrating production deviations, component serial numbers, and quality-control records, thereby moving from a design-intent model toward an asset-specific baseline.

During operation, the DT becomes a dynamic, continuously updated representation receiving sensor data, operational records, and maintenance information. This enables condition monitoring, anomaly detection, degradation estimation, and predictive maintenance. The MRO cycle creates a reciprocal relationship: maintenance actions update the DT, which in turn informs future maintenance decisions. During modernization, configuration management and modification impact assessment are supported. At the end-of-life stage, the DT informs retirement, component reuse, recycling, and knowledge transfer decisions.

Within aviation transport systems, the aircraft functions not only as a physical vehicle but as a central coordination node through which multiple stakeholders, data flows, operational responsibilities, and lifecycle decisions intersect (Figure 2). Airlines plan routes and fleet utilization around aircraft availability; MRO providers manage maintenance based on condition data; manufacturers use operational feedback to improve design; regulators supervise airworthiness and compliance; airports and air traffic management actors coordinate services around aircraft movement.

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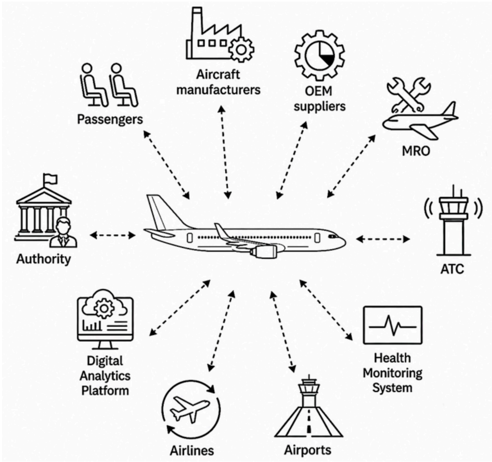

Figure 2. Aircraft as a multi-stakeholder ecosystem node in the aviation transport system.

The aircraft thus acts as a transport ecosystem interface linking physical transport functions with a distributed decision environment involving operational, technical, regulatory, economic, and environmental objectives. When represented by a digital twin, the aircraft provides a shared digital reference point through which heterogeneous stakeholders interact with the same asset while maintaining different decision views. The multi-stakeholder nature introduces governance challenges: aviation data are often commercially sensitive, safety-critical, proprietary, or subject to cybersecurity requirements, making fully centralized data sharing impractical. The DT ecosystem must support controlled data access, role-based views, traceability, and secure collaborative learning.

The aircraft digital twin ecosystem is an integrated modelling, orchestration, and decision-support environment connecting the physical aircraft, lifecycle data, analytical models, stakeholder-specific views, and planning decisions. Its structure comprises three interrelated layers (Figure 3).

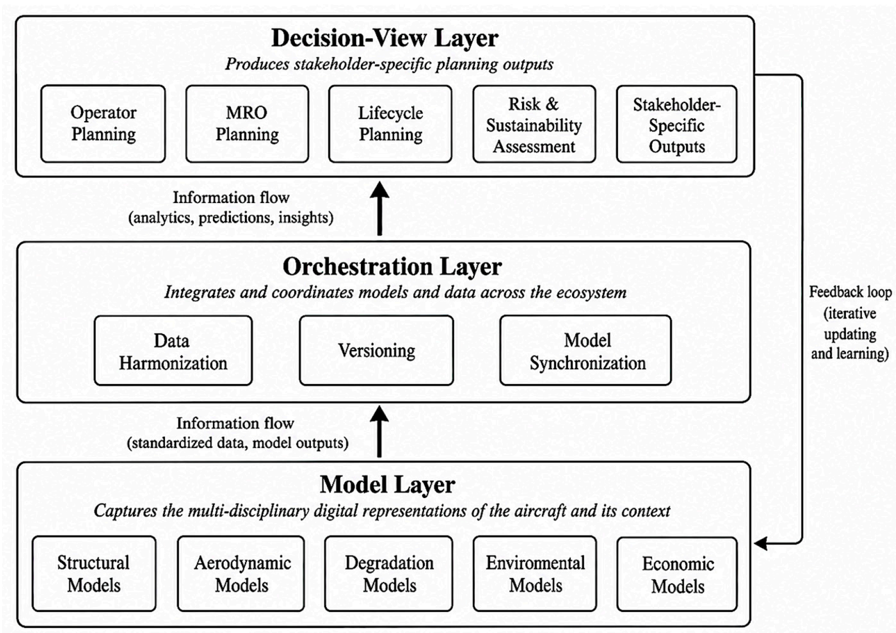

Figure 3. Three-layer structure of the aircraft digital twin ecosystem.

The model layer represents the aircraft through five complementary model families: (1) the structural model covering mechanical condition, load histories, fatigue, and structural integrity; (2) the aerodynamic model describing flight performance and fuel efficiency; (3) the component degradation model capturing wear and failure mechanisms in engines, landing gear, avionics, and other subsystems; (4) the environmental impact model evaluating the relationship between condition, operational profile, fuel consumption, and emissions; and (5) the economic analysis model translating technical states into cost, value, and resource implications.

The orchestration layer coordinates interactions among heterogeneous models, data sources, and decision processes. It manages model synchronization, configuration control, data harmonization, versioning, uncertainty handling, and sequencing of analytical tasks. The decision-view layer translates model outputs into stakeholder-specific information—pilots receive dispatch readiness and performance data; maintenance engineers receive diagnostics and workscope suggestions; fleet managers receive availability and cost indicators; regulators receive compliance evidence; OEMs receive aggregated reliability feedback.

3.2. Formal Mathematical Framework

The aircraft is represented as a lifecycle-evolving system-of-interest:

$$A(t) = \{C(t), S(t), O(t), E(t), H(t)\}$$

where $C(t)$ denotes the aircraft configuration at time t, $S(t)$ its technical state, $O(t)$ the operational profile, $E(t)$ the environmental exposure, and $H(t)$ the accumulated lifecycle history including maintenance, repairs, overhauls, modifications, and inspections.

To provide structural and computational precision, the component sets of $A(t)$ are defined over explicit mathematical spaces.

The configuration $C(t) \in \mathcal{C}$ is an element of a finite-dimensional discrete-continuous product space $\mathcal{C} = \mathbb{Z}_+{}^{\mathrm{m}} \times \mathbb{R}^{\mathrm{n}}$, where the integer subspace encodes discrete configuration attributes such as part serial numbers, installed modification states, and structural variants, and the real subspace encodes continuously valued configuration parameters such as geometric dimensions or mass properties.

The technical state $S(t) \in \mathcal{S} \subseteq \mathbb{R}^{\mathrm{p}}$ is defined on a bounded subset of p-dimensional Euclidean space, where each dimension corresponds to a measurable health indicator constrained by physical limits $\mathcal{S} = \{s \in \mathbb{R}^{\mathrm{p}} : s\_min \leq s \leq s\_max\}$.

The operational profile $O(t) \in \mathcal{O} \subseteq \mathbb{R}q$ is a time-varying vector in the operational envelope, capturing flight phase, load, speed, altitude, and environmental exposure parameters, constrained by the aircraft's certified operational boundaries.

The environmental exposure $E(t) \in \mathcal{E} \subseteq \mathbb{R}^{\mathrm{r}}$ is a vector of stochastic exogenous inputs—temperature, humidity, atmospheric corrosiveness, turbulence intensity—defined on a bounded probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

The lifecycle history $H(t)$ is represented as an ordered time-indexed record over the interval $[0,\ t] :\ H(t) = \{(\tau_{\mathrm{i}},\ a_{\mathrm{i}},\ c_{\mathrm{i}}) : \tau_{\mathrm{i}} \in [0, t],\ a_{\mathrm{i}} \in \mathcal{A}, c_{\mathrm{i}} \in \mathcal{C}\}$, where τ_{i} denotes the event timestamp, $a_{\mathrm{i}} \in \mathcal{A}$ is the maintenance or modification action drawn from a finite action vocabulary $\mathcal{A}$, and c_{i} is the configuration state recorded at that event.

The joint state space of $A(t)$ is therefore the Cartesian product

$$\mathcal{F}_A = \mathcal{C} \times \mathcal{S} \times \mathcal{O} \times \mathcal{E} \times \mathcal{H}$$

equipped with the product topology, which ensures that continuity, convergence, and proximity of system states are well-defined in the lifecycle modelling context.

Similarly, the digital twin $DT_A(t)$ is grounded in corresponding functional spaces.

The model set $M(t) = \{f_1, f_2, \ldots, f_K\}$ consists of K computable models, where each model f_K maps the joint space of technical state, operational profile, and environmental exposure to a real-valued output: $f_K : \mathcal{S} \times \mathcal{O} \times \mathcal{E} \rightarrow \mathbb{R}$.

The lifecycle data space $D(t)$ is a structured collection of square-integrable time series over $[0,\ t]$ partitioned into typed sub-spaces for sensor, operational, maintenance, environmental and configuration data streams.

The stakeholder view space $V(t) = \{V_1(t), V_2(t),\ \ldots,\ V_K(t)\}$ is a set of projections $\pi_{\mathrm{k}} : \mathcal{F}_A \times M \rightarrow \mathcal{V}_{\mathrm{k}}$, mapping the joint system-model state to role-specific information subspaces $\mathcal{V}_{\mathrm{k}}$, where $\mathcal{V}_{\mathrm{k}}$ is the subset of real-valued outputs relevant to stakeholder k. The planning output space $P(t) \subseteq \mathbb{R}^{\mathrm{n}}$ is a convex feasible set bounded by safety, regulatory, and operational constraints.

These space definitions transform the variables $A(t)$ and $DT_A(t)$ from descriptive vectors into elements of well-defined mathematical structures, making the subsequent modelling operators—model updating $U(\cdot)$, transition operator Φ_{i}, optimization objectives $J(\cdot)$, and federated aggregation—interpretable as operators on normed or topological spaces with verifiable continuity and convergence properties.

The corresponding aircraft digital twin is defined as

$$DT_A(t) = \{M(t), D(t), \Theta(t), V(t), P(t)\}$$

where $M(t)$ is the set of models, $D(t)$ the lifecycle data space, $\Theta(t)$ model parameters, $V(t)$ stakeholder-specific views, and $P(t)$ planning and management outputs. The general modelling objective is to maintain sufficient alignment between $A(t)$ and $DT_A(t)$ while generating decision outputs:

$$DT_A(t) \rightarrow P(t) = \{p_1(t), p_2(t), \ldots, p_n(t)\}$$

where $p_i(t)$ may represent maintenance plans, inspection priorities, operational recommendations, risk indicators, cost forecasts, emissions indicators, or end-of-life decisions.

Physics-based models represent aircraft behaviour using established engineering principles. In general form,

$$y_{\mathrm{ph}}(t) = f_{\mathrm{ph}}\left[x(t), u(t), \theta_{\mathrm{ph}}, \xi(t)\right]$$

where $y_{\mathrm{ph}}(t)$ is the model output, $x(t)$ the state vector, $u(t)$ operational inputs, θ_{ph} physical parameters, and $\xi(t)$ environmental conditions. The model set covers structural behaviour (M_{str}), aerodynamic performance (M_{aero}), avionics and subsystem behaviour $\left(M_{\mathrm{sys}}\right)$, and thermodynamic processes (M_{therm}). These models ensure explainability and engineering consistency essential in safety-critical contexts.

Within the proposed framework, simulation is not treated as a separate modelling category but as a computational execution mode that runs across the model set $M(t)$. A simulation model is a computable instantiation of one or more members of $M(t)$, most directly of the physics-based subfamily $\{M_{\mathrm{str}}, M_{\mathrm{aero}},\ M_{\mathrm{sys}},\ M_{\mathrm{therm}}\}$, that produces time-evolving outputs by numerically integrating the governing equations over a defined scenario envelope. The general physics-based model expression $y_{\mathrm{hyb}}(t)$ serves simultaneously as the analytical model specification and as the simulation kernel: when $x(t)$, $u(t)$ and $\xi(t)$ are supplied as time series derived from a scenario definition rather than from real-time sensor feeds, f_{ph} executes in simulation mode and generates synthetic state trajectories $y_{\mathrm{ph}}(t \mid \mathit{scenario})$, where the conditioning on "scenario" distinguishes the simulated output from the sensor-driven estimate.

Simulation models fulfil four distinct functions within the ecosystem:

- During the design phase L_{des}, the digital twin is initialized as an engineering model M_{des} supporting simulation-based evaluation of structural loads, aerodynamic performance envelopes, thermodynamic cycles, and subsystem behaviour before the physical aircraft exists.

- During operation L_{ops}, simulation models are used for what-if scenario generation: the decision output $p^*(t)$ is evaluated not only against current state $S(t)$ but also against simulated future trajectories $S_{sim}(t + \Delta t \mid p)$ under alternative maintenance or operational plans $p \in \mathcal{P}$. This enables prospective risk assessment and maintenance interval optimization without waiting for failure events to occur.
- Hybrid models $y_{\text{hyb}}(t)$ rely on physics-based simulation to provide the structural prediction component $y_{\text{ph}}(t)$ which anchors the data-driven correction term $y_{\text{dd}}(t)$ to physically consistent boundaries. Without the simulation component, the hybrid model degenerates to a purely data-driven extrapolator that may violate engineering constraints in out-of-distribution operating regimes.
- In the training and knowledge management scenario, simulation models generate synthetic lifecycle trajectories that augment sparse real-world failure datasets, supporting AI/ML model training and maintenance, personal scenario-based learning where historical event coverage is insufficient.

The integration of simulation into the ecosystem is governed by the same lifecycle transition operator Φ_i and model update operator $U(\cdot)$ that apply to all members of $M(t)$. When operational data $D(t)$ becomes available, the parameter-updating hybrid strategy

$$\theta_{ph}(t+1) = \theta_{ph}(t) + \Delta\theta[D(t)]$$

recalibrates the simulation model parameters θ_{ph} to reflect the as-operated condition of the specific aircraft, ensuring that simulation trajectories remain aligned with the physical asset rather than representing a generic fleet-average behaviour. This recalibration is the mechanism by which the digital twin maintains the fidelity of its simulation capability throughout the operational lifecycle.

Verification of simulation models follows the physics-based model verification principles, including checking of implemented equations, boundary conditions, parameter values, and numerical solvers against the intended engineering model. Simulation outputs are additionally subject to the same performance validation conditions as other model updates before being used as inputs to federate model updating, ensuring that only simulation models of sufficient predictive fidelity contribute to the shared global model.

Data-driven models learn patterns from operational and lifecycle data:

$$y_{\text{dd}}(t) = g[D(t), \theta_{\text{dd}}]$$

where

$$D(t) = \{D_{\text{sens}}(t), D_{\text{ops}}(t), D_{\text{mro}}(t), D_{\text{env}}(t), D_{\text{conf}}(t)\}$$

encompasses sensor data, operational records, maintenance histories, environmental exposure, and configuration data. Anomaly detection is expressed as

$$S(t) = \| y(t) - \hat{y}(t) \| > \tau$$

where $S(t)$ is an anomaly score, and τ is a detection threshold. Data-driven functions include anomaly detection, degradation trend identification, remaining useful life (RUL) estimation, and maintenance demand prediction.

The data-driven model subfamily is the primary carrier of advanced predictive analytics within the ecosystem and delivers four functions, each mapped to a specific output type and decision role.

Anomaly detection identifies deviations of the observed technical state from the nominal operating envelope and triggers maintenance or inspection signals when the anomaly score exceeds a detection threshold. Fault diagnosis maps observed anomaly patterns to root-cause fault classes as a probability distribution over a predefined fault taxonomy, drawing on neural network classifiers, Bayesian networks, and support vector machines [18,19,29,30]. RUL estimation produces a probabilistic forecast of remaining useful life with a confidence interval reflecting model uncertainty and operating condition variability, using long short-term memory networks, convolutional neural networks, or hybrid degradation models combining physics-based curves with data-driven correction terms [20–22,24]. Maintenance demand forecasting aggregates individual asset RUL estimates and failure probabilities into fleet-level workload predictions over a planning horizon, feeding resource and scheduling inputs to the maintenance optimization objective.

These four functions connect to the decision-support layer through the planning output: anomaly detection and fault diagnosis feed the safety and risk management scenario; RUL estimation feeds maintenance optimization and asset lifecycle planning; maintenance demand forecasting feeds economic performance and operational efficiency. In hybrid modelling mode, all four functions receive physics-based predictions as structural inputs, ensuring that data-driven outputs remain bounded by engineering-consistent constraints even under sparse or degraded sensor coverage.

Hybrid models combine physics-based and data-driven approaches:

$$y_{\text{hyb}}(t) = F\left[y_{\text{ph}}(t), y_{\text{dd}}(t), \omega(t)\right]$$

Three hybrid strategies are applicable. The residual-learning approach trains the data-driven component on the difference between physics-based predictions and observations:

$$y_{\text{hyb}}(t) = y_{\text{ph}}(t) + r(t)$$

The parameter-updating approach calibrates physics-based model parameters with operational data:

$$\theta_{\text{ph}}(t+1) = \theta_{\text{ph}}(t) + \Delta\theta[D(t)]$$

The constraint-informed machine learning approach penalizes violations of physical constraints during data-driven training, balancing empirical fit with physical consistency.

The aircraft lifecycle is represented as a sequence of phases

$$L = \left\{L_{\text{des}}, L_{\text{man}}, L_{\text{ops}}, L_{\text{mro}}, L_{\text{mod}}, L_{\text{eol}}\right\}$$

At each phase L_i, the digital twin is characterized by specific combinations of data, models, parameters, and decision outputs. The lifecycle transition operator is

$$DT_A^{L_{i+1}}(t) = \Phi_i\left\{DT_A^{L_i}(t), D_{L_{i+1}}^{\text{new}}(t), A_{L_i}^{\text{dec}}(t)\right\}$$

where Φ_i is the transition operator, $D_{L_{i+1}}^{\text{new}}(t)$ captures new data introduced in the next phase, and $A_{L_i}^{\text{dec}}(t)$ denotes decisions taken in the previous phase. This formulation emphasizes that the digital twin is progressively transformed by new evidence, configuration changes, and management decisions.

During the design phase, the DT is initialized as an engineering model (M_{des}) supporting simulation-based evaluation and early lifecycle decisions. During manufacturing, the transition to the as-built baseline

$$DT_A^0 = \{D_{\text{man}}, M_{\text{man}}, \Theta_{\text{man}}, C_0\}$$

establishes the foundation for subsequent operational tracking. During operation, continuous support-phase updating synchronizes the DT with the physical aircraft via

$$\Theta(t+1) = U[\Theta(t), D_t]$$

where $U(\cdot)$ is the model update operator and D_t is preprocessed lifecycle data. During the usage phase, the DT generates actionable outputs. The expected time to failure and the remaining useful life are

$$T_f(t) = \mathbb{E}\left[T_f \mid D_t, \Theta(t)\right]$$
$$RUL(t) = T_f(t) - t.$$

Operational and management decisions are formulated as

$$p^*(t) = \arg\min_{p \in P} J(p,t),$$

where the sustainability-oriented objective function is

$$J(p,t) = w_c C(p,t) + w_r R(p,t) + w_d Dwn(p,t) + w_e Ems(p,t) + w_s Res(p,t) \tag{1}$$

with C denoting cost, R risk, Dwn downtime, Ems emissions impact, Res resource use and w_i stakeholder-defined weighting coefficients.

The lifecycle decision problem is formally a multi-objective optimization problem over a vector-valued objective, the components of which are incommensurable in units and partially conflicting in direction. Let the decision variable $p \in \mathcal{P} \subseteq \mathbb{R}^{\mathrm{n}}$ represent a lifecycle action plan—a maintenance schedule, operational assignment, or resource allocation defined over the feasible set $\mathcal{P}$. The full vector-valued objective at time t is

$$\boldsymbol{F}(p,\ t) = [C(p,t),\ R(p,t),\ Dwn(p,t),\ Ems(p,t),\ Res(p,t)]^{\mathrm{T}} \in \mathbb{R}^5$$

where each component constitutes a distinct decision criterion: $C(p,t)$ is the total lifecycle cost over the planning horizon, $R(p,t)$ is the probability-weighted risk of unplanned failure or safety event, $Dwn(p,t)$ is the opportunity cost of aircraft unavailability, $Ems(p,t)$ is the degradation-induced emissions penalty expressed in CO_2-equivalent units and $Res(p,t)$ is the material and labour resource consumption. The set of Pareto-optimal solutions $\mathcal{P}* \subseteq \mathcal{P}$ is defined as

$$\begin{aligned}\mathcal{P}* = \{p \in \mathcal{P} :\ \ & \nexists p' \in \mathcal{P}\ such\ that\ \boldsymbol{F}(p',\ t) \\ & \leq \boldsymbol{F}(p,\ t)\ componentwise,\ with\ at\ least\ one\ strict\ inequality\}\end{aligned}$$

Since Pareto-optimal solutions cannot be ranked without stakeholder preferences, the multi-objective problem is reduced to a scalar form through a weighted aggregation over $\mathcal{P}$*, yielding the decision objective already stated in Equation (1)

$$J(p,\ t) = wc\ C(p,t) + wr\ R(p,t) + wd\ Dwn(p,t) + we\ Ems(p,t) + ws\ Res(p,t)$$

subject to the constraint that weights are normalized: $wc + wr + wd + we + ws = 1$, $w_{\mathrm{i}} \geq 0\ \forall i$.

The weighting vector $\boldsymbol{w} = [wc,\ wr,\ wd,\ we,\ ws]^{\mathrm{T}}$ is not universal. It is stakeholder-defined and lifecycle-phase-dependent. Table 1 specifies the interpretive mapping of each weight to its decision domain and the actor group for whom it is primary.

Table 1. Multi-objective decision criteria of the lifecycle optimization problem.

Criterion	Symbol	Decision Domain	Primary Stakeholder	Lifecycle Phase Sensitivity
Lifecycle cost	wc	MRO budgeting, fleet investment	Airline, MRO provider	High in operation and MRO phases
Safety and failure risk	wr	Airworthiness, structural integrity	Regulator, airline safety	Dominant near end-of-life and high-cycle components
Downtime opportunity cost	wd	Fleet scheduling, dispatch reliability	Airline operations	High during peak utilization periods
Emission impact	we	Fuel burn, CO_2 and NO_x penalty	Airline sustainability, regulator	Increasing weight under net-zero trajectories
Resource use	ws	Spare parts, labour, material consumption	MRO provider, OEM	High in heavy maintenance events

The feasible set $\mathcal{P}$ is bounded by three classes of constraints. Safety constraints enforce minimum airworthiness margins:

$$R(p,\ t)\ \leq\ R_{max},\ SM(p,\ t)\ \geq\ SM_{min}$$

where R_{max} is the maximum admissible failure probability derived from safety case requirements and SM_{min} is the minimum structural or performance safety margin. These constraints are inviolable and are satisfied prior to any cost or sustainability trade-off evaluation; they define the boundary of the admissible region within $\mathcal{P}$ and cannot be relaxed by adjusting the weighting vector $\boldsymbol{w}$.

Operational constraints enforce continuity of transport service:

$$Av(p,\ t)\ \geq\ Av_{min},\ Sched(p,\ t)\ \in\ \mathcal{F}_{sched}$$

where Av_{min} is the minimum required fleet availability and $\mathcal{F}_{sched}$ is the set of schedule-feasible maintenance windows. Sustainability constraints encode emissions and resource budgets:

$$Ems(p,\ t)\ \leq\ Ems_{budget}(t),\ Res(p,\ t)\ \leq\ Res_{budget}(t)$$

where $Ems_{budget}(t)$ is a time-varying emissions allocation derived from operator-level net-zero commitments aligned with ICAO LTAG targets [2,3], and $Res_{budget}(t)$ is the available material and labour envelope for the planning period.

The constrained scalar problem is therefore

$$p*(t) = arg\ min\_\{p\ \in\ \mathcal{P}_{adm}\}\ J(p,\ t)$$

where the admissible feasible set $\mathcal{P}_{adm} \subseteq \mathcal{P}$ is

$$\mathcal{P}_{adm} = \{p\ \in\ \mathcal{P} : R(p,t)\ \leq\ R_{max},\ SM(p,t)\ \geq\ SM_{min},\ Av(p,t) \geq\ Av_{min},\ Sched(p,t) \\ \in \mathcal{F}_{sched},\ Ems(p,t)\ \leq\ Ems_{budget}(t),\ Res(p,t)\ \leq\ Res_{budget}(t)\}$$

This formulation makes explicit the hierarchical priority structure of the decision problem. Safety constraints define the outer boundary of $\mathcal{P}_{adm}$ and are non-negotiable. Operational constraints ensure transport-system continuity. Sustainability constraints impose environmental and resource limits consistent with lifecycle governance obligations. Within $\mathcal{P}_{adm}$, the weighted objective $J(p,t)$ resolves the remaining trade-off among cost efficiency, risk exposure, downtime, emissions, and resource use according to the stakeholder-specific preference vector $\boldsymbol{w}$.

The relationship between the maintenance planning objective $J_m(pm,\ t)$ and the sustainability management objective $J_{SM}(SM,\ t)$ introduced later in this section follows the same hierarchical logic. Maintenance optimization operates within the inner feasible set $\mathcal{P}_{adm}$ and generates the primary planning output $p^*(t)$. The sustainability objective J_{SM} then evaluates the lifecycle-level consequence of the selected plan across emissions, fuel, resource, waste, lifecycle extension, and residual value dimensions. This two-level structure ensures that short-horizon maintenance decisions remain consistent with long-horizon sustainability objectives and that the digital twin ecosystem can produce both operationally actionable recommendations and lifecycle-level sustainability evidence within a single coherent decision framework.

Raw data sharing in aviation is constrained by ownership, certification, cybersecurity, and regulatory requirements. Federated learning enables collaborative model improvement without centralizing sensitive data. The ecosystem consists of K stakeholder nodes, including airlines, MRO providers, OEMs, regulators, and airports, each maintaining a local dataset $D_k(t)$ and training a local model:

$$M_k(t) = g_k[D_k(t), \theta_k(t)]$$

The local loss function is minimized to produce local model updates $\Delta\theta_k(t)$. These updates are transmitted to a global aggregation layer:

$$\theta_G(t+1) = \sum_{k=1}^{K} w_k(t)\ \theta_k(t+1)$$

where the weighting coefficient $w_k(t)$ reflects data quality $q_k(t)$, operational relevance $r_k(t)$ and validation trust score $s_k(t)$:

$$w_k(t) = \frac{q_k(t)\ r_k(t)\ s_k(t)}{\sum_{j=1}^{K} q_j(t)\ r_j(t)\ s_j(t)}$$

A local update is accepted only if

$$Perf_k(\theta_k) \geq Perf_{\min}$$

$$Risk_k(\theta_k) \leq Risk_{\max}$$

$$Drift_k(\theta_k, \theta_G) \leq \delta_k$$

This validation gate prevents error propagation from unreliable local nodes.

The federated update operates exclusively at the level of parameter increments. Each node k computes a local gradient $\nabla\mathcal{L}_k(\theta_k)$ over its private dataset $D_k(t)$ and transmits only the differentially private perturbation:

$$\widetilde{\Delta\theta}_k(t) \ = \ \Delta\theta_k(t) \ + \ \mathcal{N}(0,\ {\sigma_k}^2 \cdot \boldsymbol{I})$$

where $\boldsymbol{I} \in \mathbb{R}\{s \times s\}$ is the identity matrix, $s \ = \ dim(\theta_k)$, and σ_k is calibrated to the $(\varepsilon_k, \delta_k)$-differential privacy budget. Raw FDR records, sensor streams, and maintenance tracking data remain local and cannot be reconstructed from $\widetilde{\Delta\theta}_k(t)$ with probability bounded by δ_k. The global update then becomes

$$\theta_G(t+1) = \theta_G(t) + \sum_{k\ \in\ \mathcal{A}(t)} w_k(t) \cdot \widetilde{\Delta\theta}_k(t)$$

where $\mathcal{A}(t) \subseteq \{1, \ldots, K\}$ is the set of nodes admitted by the validation gate at round t.

Stakeholders have partially conflicting objectives: an airline seeks to extend time-on-wing, while an OEM may protect proprietary wear models and enforce shorter maintenance intervals. The governance layer addresses this through two mechanisms. First, the contribution weight $w_k(t)$—already defined above as a function of data quality $q_k(t)$, operational relevance $r_k(t)$, and trust score s_k—creates a reciprocal incentive: influence over the global model is proportional to the quality of the update contributed. A stakeholder who withholds informative updates or adds excessive noise receives lower $w_k(t)$ and therefore derives less benefit from the shared model. Second, an influence cap $w_k(t) \leq w_{max} = 1/K_{min}$ prevents any dominant actor from unilaterally steering the global model toward its proprietary parameter region.

To detect strategic drift that passes the standard validation gate, the governance layer additionally computes a consensus divergence score:

$$CD_k(t) = \|\theta_k(t) - \theta_G(t)\| - (1/K)\sum_j \|\theta_j(t) - \theta_G(t)\|$$

where $\|\cdot\|$ denotes the Euclidean norm of the parameter difference vector.

If $CD_k(t) > \gamma_{CD}$, the update is quarantined pending independent audit by a designated validation authority, without requiring disclosure of raw data or proprietary model internals. Here, $\gamma_{CD} > 0$ is a governance-defined consensus divergence threshold, set by the validation authority to reflect the maximum admissible deviation of a local update from the fleet-wide consensus before an independent audit is triggered.

The lifecycle-context-aware aggregation further conditions updates on the lifecycle phase L_i, aircraft configuration $C(t)$ and data quality $Q(t)$, ensuring that data from operationally dissimilar aircraft or post-maintenance recovery periods do not corrupt shared models.

Figure 4 illustrates the federated learning architecture and the flow of local updates through validation, aggregation, and redistribution to authorized stakeholders. It illustrates how collaborative model improvement can be achieved without centralizing sensitive aviation data. Each stakeholder trains local digital twin models using its own operational, maintenance, or technical datasets. Only model updates or parameters are submitted to the validation layer, where their consistency, quality, and security are checked before global aggregation. The updated global model is then redistributed to authorized participants, enabling continuous learning while preserving data ownership, cybersecurity constraints, and stakeholder-specific access rights.

The maintenance planning output is formulated as an optimization problem:

$$p_m^*(t) = \arg\min_{p_m \in P_m} J_m(p_m, t)$$

where the objective J_m balances direct maintenance cost $C_m(p_m, t)$, opportunity cost from downtime $Dwn(p_m, t)$, unplanned failure risk $R_f(p_m, t)$, spare-part logistics cost $Sp(p_m, t)$ and regulatory compliance penalty $\Pi(p_m, t)$, subject to safety margin, resource and scheduling constraints. The maintenance strategy is

$$\begin{aligned} &MS(t) \\ &= \{InspectionPlan(t), Workscope(t), SpareParts(t), Resources(t), RiskControls(t)\}. \end{aligned}$$

The operational optimization output supports route assignment, fuel loading, schedule planning, and fleet allocation:

$$p_o^*(t) = \arg \max_{p_o \in P_o} [w_a Av(p_o, t) + w_f FuelEff(p_o, t) + w_e OpsEff(p_o, t) + w_r Rel(p_o, t)]$$

which is subject to safety margin, regulatory compliance, and aircraft condition constraints. This formulation connects aircraft technical condition directly with transport-system performance.

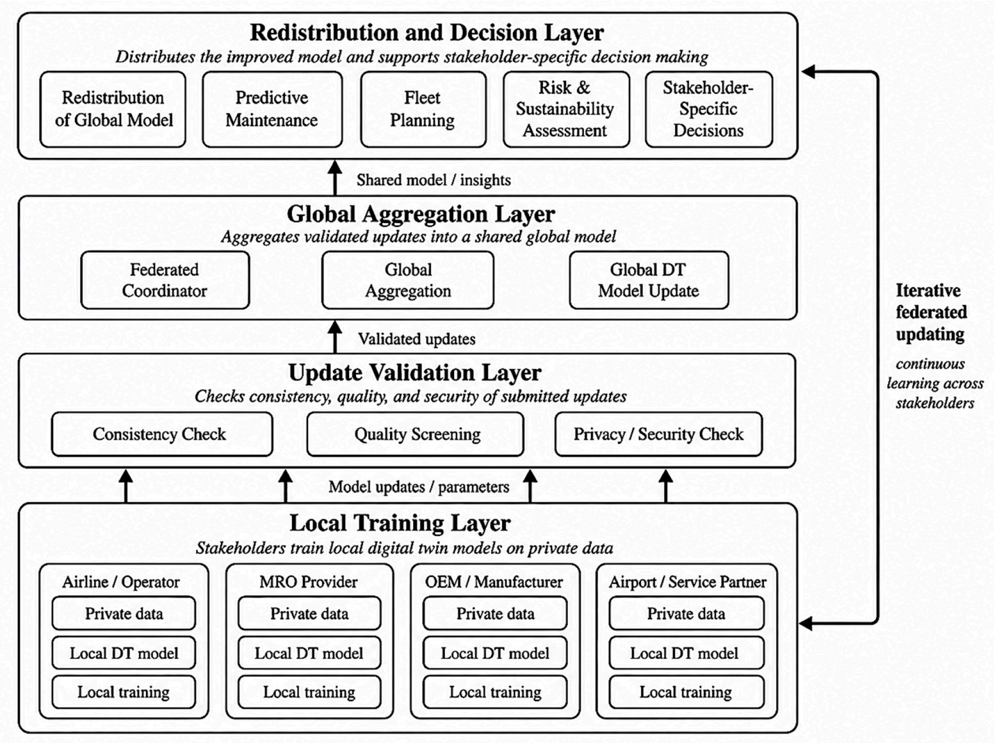

Figure 4. Federated learning architecture for multi-stakeholder aircraft digital twin model updating.

The sustainability management objective integrates environmental, resource, and lifecycle value dimensions:

$$SM^*(t) = \arg \min_{SM \in \mathcal{S}} J_{SM}(SM, t)$$

$$J_{SM}(SM, t) = c_1 Ems(t) + c_2 Fuel(t) + c_3 Res(t) + c_4 Waste(t) - c_5 Life(t) - c_6 Value(t) \quad (2)$$

where Ems denotes emissions, $Fuel$ fuel consumption, Res resource use, $Waste$ maintenance waste, $Life$ lifecycle extension benefit, and $Value$ residual asset value. The digital twin provides evidence-based estimates of how alternative decisions influence each term, enabling explicit trade-off analysis between, for example, early component replacement, associated with higher material use and lower emissions penalty, and deferred replacement, associated with lower material use and higher degradation-induced fuel burn.

3.3. Decision-Support Scenarios Across the Aircraft Lifecycle

The proposed framework enables eight categories of decision-support scenarios across the aircraft lifecycle, illustrated in Figure 5. It positions the aircraft digital twin as a decision-support core that integrates lifecycle data, model-based analytics, predictive insights, and stakeholder views. The surrounding scenarios show that the digital twin is not limited to predictive maintenance but can support a broader set of lifecycle decisions. These include maintenance optimization, operational efficiency, safety and risk management, asset and lifecycle planning, economic performance, regulatory compliance, training and knowledge management, and environmental sustainability. The lifecycle band indicates that these functions remain relevant across design, operation, maintenance, upgrade, and end-of-life phases.

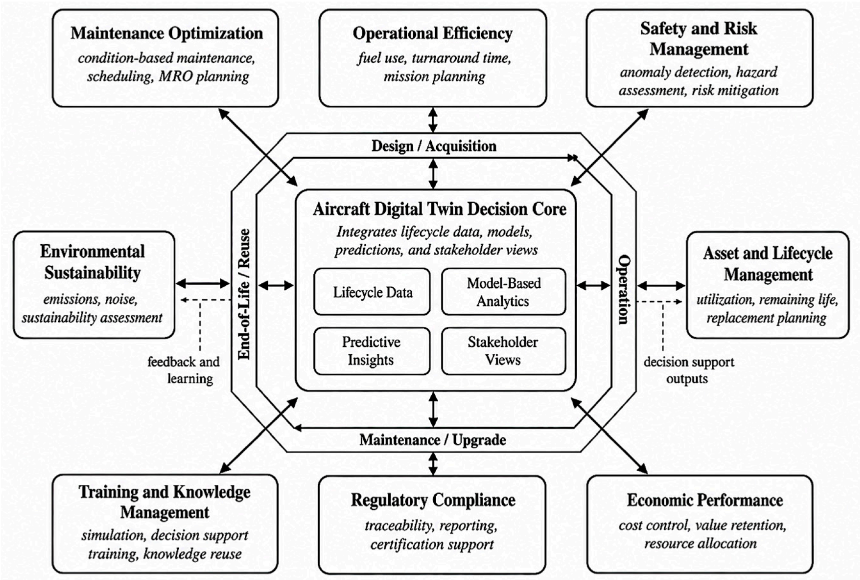

Figure 5. Decision-support scenarios enabled by aircraft digital twins across the lifecycle, linking the aircraft digital twin decision core with maintenance, operations, safety, lifecycle, economic, regulatory, training, and sustainability applications.

Table 2 summarizes each scenario, its digital twin function, and its planning and management output.

Table 2. Decision-support scenarios of aircraft digital twins associated with digital twin functions, and planning/management outputs.

Scenario	Key DT Function	Planning/Management Output
Maintenance optimization	Degradation prediction, RUL estimation, anomaly detection	Condition-based inspection plans, workscope optimization, spare-part pre-positioning
Operational efficiency	Performance monitoring, flight-profile optimization	Route assignment, fuel loading, dispatch reliability indicators
Safety and risk management	Failure probability estimation, structural integrity assessment	Risk-based inspection scheduling, safety margin monitoring
Asset and lifecycle management	Lifecycle state tracking, configuration management	Modernization decisions, end-of-life planning, residual value assessment
Economic performance	Lifecycle cost forecasting, trade-off analysis	Investment decisions, fleet acquisition, resource allocation
Regulatory compliance	Airworthiness documentation, compliance evidence generation	Audit trails, certification support, regulatory reporting
Training and knowledge management	Historical event analysis, simulation scenario generation	Training scenario design, maintenance knowledge transfer
Environmental sustainability	Emissions and fuel-burn estimation, lifecycle resource tracking	Eco-efficient operations, green maintenance planning, end-of-life recycling decisions

The maintenance optimization scenario generates condition-based maintenance plans that replace fixed-interval schedules with evidence-driven decisions. The operational efficiency scenario improves aircraft assignment, route planning, and dispatch reliability. The safety and risk management scenario provides quantitative risk indicators that support both proactive intervention and regulatory compliance. The asset and lifecycle management scenario enables condition-aware decisions about modernization, component reuse, and retirement timing.

The economic performance scenario translates technical conditions into lifecycle cost estimates, supporting fleet investment and resource allocation decisions. The regulatory compliance scenario provides traceable, audit-ready evidence of airworthiness, configuration state, and maintenance history. The training and knowledge management scenario uses historical event data to build simulation scenarios and preserve institutional knowledge. The environmental sustainability scenario connects technical conditions with emissions indicators, enabling eco-efficient operations and lifecycle-oriented environmental management.

3.4. Reference Architecture and Adoption Maturity

The aircraft digital twin ecosystem reference architecture comprises four functional layers. Figure 6 provides an ecosystem-level reference architecture for implementing the proposed framework. The data acquisition layer collects information from aircraft sensors, onboard systems, maintenance records, operational datasets, environmental sources, and external databases. The model orchestration layer harmonizes these data streams and manages the digital twin model repository, synchronization, lifecycle analytics, versioning, and governance. The decision-support layer converts models and analytics into predictive maintenance, operational optimization, risk assessment, asset planning, and sustainability outputs. Finally, the stakeholder interface layer provides role-specific views for airlines, MRO providers, OEMs, airports, service partners, and regulators. Federated learning and multi-stakeholder connectivity are represented as cross-cutting mechanisms because they enable distributed collaboration, secure model updating, and iterative ecosystem learning.

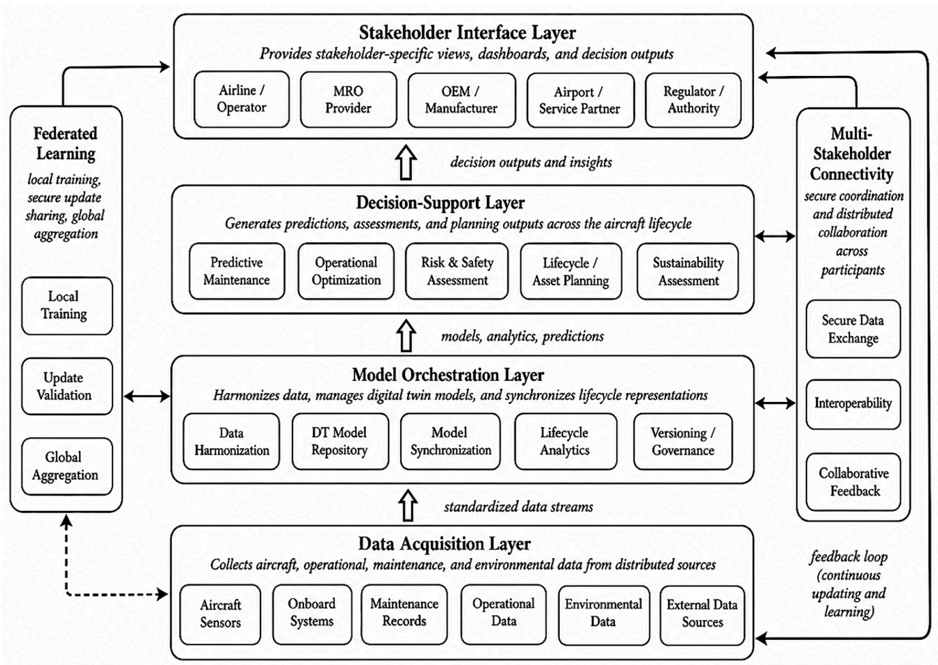

Figure 6. Reference architecture of the aircraft digital twin ecosystem.

The data acquisition and integration layer interfaces with onboard systems, including flight data recorders, health and usage monitoring systems, and avionics networks; ground systems, including maintenance information systems and airport operations databases; and external sources, including OEM reliability databases, regulatory archives, and supplier data. The layer handles preprocessing, quality control, harmonization, and real-time ingestion.

The model orchestration layer manages the following lifecycle data pipeline:

$$\textit{Data Sources} \rightarrow \textit{Preprocessing} \rightarrow \textit{Model Updating} \rightarrow \textit{Decision Support} \rightarrow \textit{Feedback}$$

It coordinates version control of physics-based models, artificial intelligence/machine learning (AI/ML) training and retraining cycles, federated update aggregation, and uncertainty propagation. The decision-support layer hosts planning modules for maintenance, operations, fleet management, compliance, and sustainability. The stakeholder interface layer provides role-based, purpose-driven access through dashboards, APIs, notification systems, and integration with enterprise resource planning and maintenance management systems.

A critical architectural element is the lifecycle governance structure:

$$\mathrm{GOV} = \{R_{\mathrm{data}}, R_{\mathrm{access}}, R_{\mathrm{model}}, R_{\mathrm{valid}}, R_{\mathrm{audit}}\}$$

where R_{data} denotes data-sharing and data-quality rules, R_{access} access-control and authorization rules, R_{model} model update and version-control rules, R_{valid} validation and acceptance rules, and R_{audit} auditability and traceability rules. This structure governs data sharing, access control, model update authority, validation requirements, and audit traceability, ensuring that digital twin outputs remain trustworthy and attributable across organizational boundaries.

In lifecycle-oriented aircraft digital twin ecosystems, verification and validation (V&V) is particularly complex because the system integrates physics-based models, AI/ML models, hybrid models, simulation engines, data pipelines, and federated learning. Figure 7 groups the main verification and validation techniques required for trustworthy aircraft digital twin deployment. Physics-based model verification ensures that analytical and simulation-based models are structurally consistent, correctly parameterized, and sensitive to relevant boundary conditions. AI/ML validation addresses dataset quality, predictive accuracy, robustness, uncertainty, and explainability. Software and system-integration testing focuses on interfaces, data pipelines, synchronization mechanisms, cybersecurity, and reliability. Federated learning governance adds another assurance layer by controlling local update validation, aggregation rules, privacy protection, auditability, and traceability. Together, these techniques support continuous assurance throughout the digital twin lifecycle.

Verification checks whether the digital twin and its models have been built correctly. For physics-based models, verification involves checking implemented equations, boundary conditions, parameter values, and numerical solvers against the intended engineering model. For software components, verification includes unit testing, integration testing, interface testing, and conformance with aviation software standards.

Validation checks whether the correct digital twin was built, that is, whether the DT adequately represents physical aircraft behaviour under realistic operational conditions. A basic validation metric may be expressed as

$$e_{\mathrm{val}}(t) = \| y_{\mathrm{real}}(t) - y_{\mathrm{DT}}(t) \| \leq \varepsilon_{\mathrm{val}}$$

where $e_{\mathrm{val}}(t)$ denotes the validation error at time t, $y_{\mathrm{real}}(t)$ is the observed output of the physical aircraft or subsystem, $y_{\mathrm{DT}}(t)$ is the corresponding digital twin output, and $\varepsilon_{\mathrm{val}}$ is the admissible validation threshold.

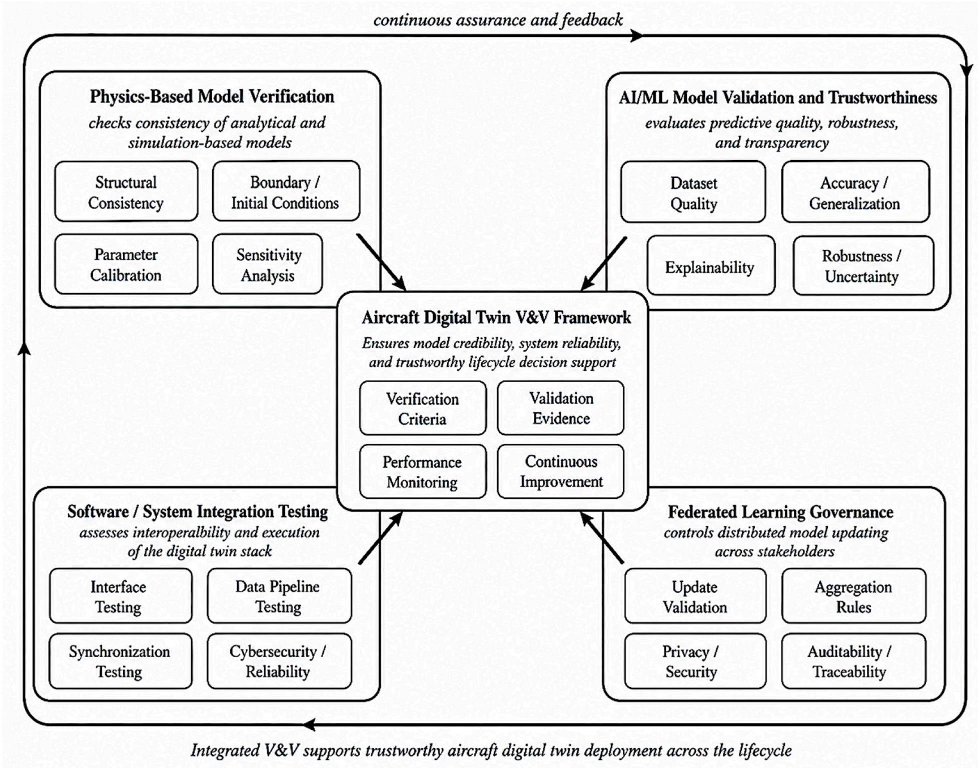

Figure 7. Validation and verification techniques for aircraft digital twins.

Validation procedures include historical replay validation, cross-validation with operational data, physical twin synchronization checks, expert validation, OEM benchmark comparison, and post-action outcome validation. These procedures form a closed assurance loop:

$$Prediction \rightarrow Action \rightarrow Observed\ Outcome \rightarrow Validation \rightarrow Model\ Update$$

AI model trustworthiness depends on performance, explainability, robustness, uncertainty quantification, data quality, traceability, and governance. Data drift monitoring detects distribution shifts between training and operational data. In general form, drift may be represented as

$$\text{Drift}\left(D_{\text{train}}, D_{\text{ops}}\right) > \delta_{\text{drift}}$$

where D_{train} denotes the training-data distribution, D_{ops} denotes the operational-data distribution, and δ_{drift} is the allowable drift threshold.

Uncertainty quantification provides prediction bounds around the model output:

$$\hat{y}(t) \pm U(t)$$

where $\hat{y}(t)$ is the predicted output, and $U(t)$ denotes the uncertainty bound associated with the prediction. In decision-support applications, the uncertainty-aware output may therefore be represented as

$$P(t) = \{\hat{y}(t), U(t), Conf(t)\}$$

where $Conf(t)$ denotes the confidence level or trust indicator associated with the digital twin output.

For federated digital twin ecosystems, rollback capability to a previously validated model version is essential if an update degrades performance or produces unsafe recommendations. Let $\theta_G^{(v)}$ denote the global model parameters at validated version v. A rollback operation can be represented as

$$\theta_G(t+1) \leftarrow \theta_G^{(v)} \text{ if } Perf(\theta_G(t+1)) < Perf_{\min} \text{ or } Risk(\theta_G(t+1)) > Risk_{\max}$$

This ensures that unsafe or poorly performing global updates do not propagate through the aircraft digital twin ecosystem.

Digital twin ecosystems are not deployed at full capability in a single step. Table 3 presents a five-level maturity model describing the evolutionary path from basic monitoring to adaptive lifecycle management.

Table 3. Five-level maturity model for aircraft digital twin ecosystem adoption.

Level	Designation	Capability	Decision Output	Adoption Prerequisite
1	Monitoring	Sensor data acquisition and condition dashboards	Alerts and status reports	Data connectivity, basic sensors
2	Diagnostic	Fault detection, anomaly classification, root-cause analysis	Maintenance triggers, event reports	Data quality management, analytics platform
3	Predictive	Degradation forecasting, RUL estimation, failure probability	Predictive maintenance schedules	Validated ML/hybrid models, historical data
4	Prescriptive	Optimization of maintenance, operations, and resource allocation	Recommended action plans	Multi-stakeholder integration, optimization engines
5	Adaptive	Federated learning, lifecycle governance, sustainability integration	Supervised-autonomous lifecycle management	Governance framework, regulatory acceptance, V&V lifecycle process

In safety-critical aviation contexts, progression through maturity levels requires evidence-based validation at each stage. Digital twin outputs should be introduced progressively from advisory (Levels 1–2) through predictive and prescriptive (Levels 3–4) to supervised-autonomous functions (Level 5). This progression also aligns with regulatory acceptance processes, where each new capability requires demonstrated reliability, explainability, and governance before influencing safety-relevant decisions.

3.5. Illustrative Numerical Instantiation of the Framework

To illustrate how the formal constructs introduced in Section 3.2 can be instantiated, this section presents a simplified numerical example. The example uses synthetic but physically motivated data and is intended only to demonstrate the traceability of the proposed framework from state estimation to maintenance planning, federated model updating, and sustainability assessment. It should not be interpreted as an operational case study or as a validated engine-performance model.

The illustrative logic of the example is summarized in Figure 8. The figure shows how the digital twin ecosystem transforms hybrid state estimation into a maintenance decision, how the resulting maintenance event generates post-action data for federated model updating, and how the decision is subsequently evaluated from a sustainability perspective.

Consider a narrowbody aircraft operating a medium-haul route. The asset of interest is the high-pressure turbine (HPT) module of a turbofan engine. The digital twin ecosystem is assumed to have reached the predictive maturity level, meaning that validated degradation-tracking and remaining useful life estimation models are available. The current cycle counter is $t = 780$ flight cycles (FC), and three maintenance options are considered:

$$p_1 : t = 800 \text{ FC}, \ p_2 : t = 950 \text{ FC}, \ p_3 : t = 1100 \text{ FC}$$

The technical state of the HPT module is estimated using the hybrid modelling structure introduced earlier:

$$y_{\text{hyb}}(t) = F[y_{\text{ph}}(t), y_{\text{dd}}(t), \omega(t)]$$

where $y_{\text{ph}}(t)$ is the physics-based estimate, $y_{\text{dd}}(t)$ is the data-driven estimate, and $\omega(t)$ denotes the fusion weights. In this example, the physics-based thermodynamic model estimates the exhaust gas temperature (EGT) margin as $y_{\text{ph}}(780) = 5.1\ ^\circ\text{C}$. A hypothetical data-driven model trained on representative fleet data provides $y_{\text{dd}}(780) = 6.3\ ^\circ\text{C}$.

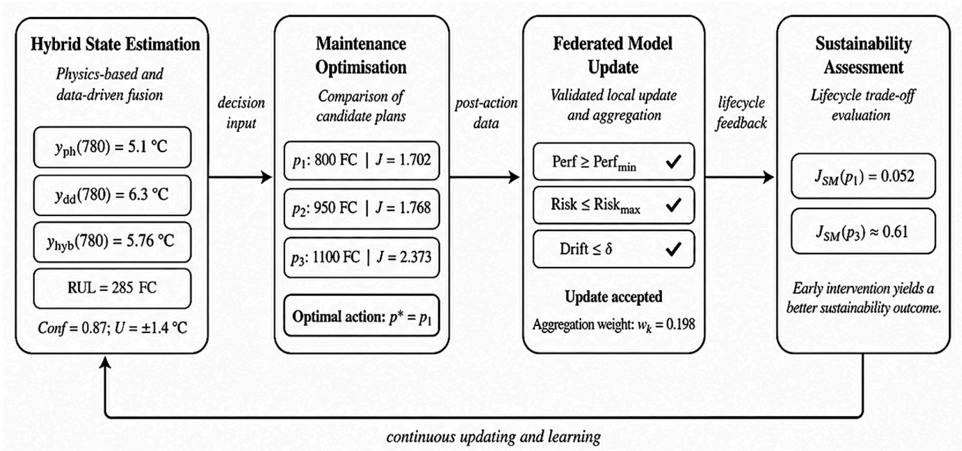

Figure 8. Illustrative numerical instantiation of the aircraft digital twin framework for HPT maintenance planning.

Using validation-confidence weights $\omega(780) = [0.45, 0.55]$, the hybrid estimate becomes

$$y_{\text{hyb}}(780) = 0.45 \cdot 5.1 + 0.55 \cdot 6.3 = 5.76\ ^\circ\text{C}.$$

With an uncertainty bound of $U(780) = \pm 1.4\ ^\circ\text{C}$, the digital twin output is expressed as

$$P(780) = \{5.76\ ^\circ\text{C}, \pm 1.4\ ^\circ\text{C}, Conf(780) = 0.87\}.$$

The remaining useful life is estimated as

$$T_f(780) = \mathbb{E}\Big[T_f \mid D_t, \Theta(780)\Big] \approx 1065\ \text{FC}$$

$$RUL(780) = T_f(780) - 780 = 285\ \text{FC}$$

The estimated RUL interval is assumed to be $210 - 360$ FC, reflecting model uncertainty and variability in operating conditions.

The maintenance decision is formulated using the sustainability-oriented objective function from Equation (1). The weighting coefficients are set as

$$w_c = 0.35, w_r = 0.25, w_d = 0.20, w_e = 0.12, w_s = 0.08$$

reflecting an airline policy that prioritizes cost control and risk management while retaining explicit sustainability terms.

Table 4 summarizes the objective components for the three candidate maintenance plans. To enable comparison across heterogeneous dimensions—cost, risk, downtime, emissions, and resource use—each component is expressed on a dimensionless synthetic scale from 0 to 5, where 0 denotes the most favourable outcome and 5 the least favourable outcome on that dimension. The scale values are derived by normalizing physically motivated synthetic estimates against a reference baseline defined for each component: direct maintenance cost is referenced against the estimated cost of a scheduled shop visit at the nominal interval; unplanned failure risk is referenced against the probability-weighted cost of an unscheduled event derived from representative fleet statistics; downtime opportunity cost is referenced against the revenue loss associated with an average unplanned removal; emissions impact is referenced against the degradation-induced fuel-burn penalty accumulated over the residual flight cycles; and resource use is referenced against the material and labour consumption of a standard workscope. All reference values are illustrative and calibrated to produce plausible relative orderings consistent with the RUL estimate and the operating context described above. They are not derived from proprietary airline or MRO data and should not be interpreted as absolute cost or risk figures. The purpose of the table is to demonstrate the traceability and interpretability of the proposed decision framework, rather than to quantify the maintenance economics of a specific aircraft type or operator.

Table 4. Estimated objective components and optimization results for candidate HPT maintenance plans.

Objective Component	Weight	p_1: 800 FC	p_2: 950 FC	p_3: 1100 FC
Direct maintenance cost $C(p,t)$	0.35	3.20	2.85	2.65
Unplanned failure risk $R(p,t)$	0.25	0.40	1.20	3.85
Downtime opportunity cost $Dwn(p,t)$	0.20	1.80	1.55	1.30
Emissions impact $Ems(p,t)$	0.12	0.55	0.90	1.45
Resource use $Res(p,t)$	0.08	0.70	0.65	0.60
Objective value $J(p,t)$	—	1.702	1.768	2.373

The resulting decision is

$$p^*(780) = \arg\min_{p \in P} J(p, 780) = p_1.$$

Thus, HPT restoration at $t = 800$ FC is selected as the preferred maintenance action. Although this option has the highest direct maintenance cost, it substantially reduces risk exposure and degradation-induced emissions compared with later intervention. This illustrates that a lifecycle-oriented objective function can select an earlier intervention when safety, reliability, and sustainability penalties outweigh the apparent savings from deferral.

After the maintenance event, the aircraft returns to service with an updated configuration $C(800)$. The event generates new evidence, including post-restoration EGT margin, actual wear measurements, and replaced-part information. These data update the local digital twin parameters $\Theta_k(800)$. In the federated learning architecture, the local stakeholder node submits a model update $\Delta\theta_k(800)$, which is accepted only if the validation gate is satisfied:

$$Perf_k(\theta_k) \geq Perf_{\min}, Risk_k(\theta_k) \leq Risk_{\max}, Drift_k(\theta_k, \theta_G) \leq \delta_k.$$

For this example, the validation results are

$$0.91 \geq 0.85,\ 0.04 \leq 0.10,\ 0.07 \leq 0.15.$$

The local update is therefore accepted. If the ecosystem includes $K = 5$ participating nodes, the contribution of this node to the global aggregation can be expressed as

$$w_k(800) = \frac{q_k r_k s_k}{\sum_{j=1}^{K} q_j r_j s_j} = \frac{0.92 \cdot 0.88 \cdot 0.91}{3.71} \approx 0.198.$$

The accepted update contributes to the global degradation model without requiring the airline to share raw sensor or maintenance data. This illustrates the governance value of federated learning in multi-stakeholder aviation digital twin ecosystems.

Finally, the sustainability implication of the selected plan can be evaluated using the sustainability management objective from Equation (2). For the selected plan p_1, the illustrative estimate is

$$J_{SM}(p_1, 800) = 0.052.$$

This near-zero value indicates that the environmental and resource costs of the maintenance action are largely offset by lifecycle-extension and residual-value benefits. By contrast, a delayed intervention such as p_3 would increase degradation-related fuel-burning and emission penalties, leading to a less favourable sustainability outcome.

Table 5 consolidates the main outputs of the illustrative instantiation.

Table 5. Summary of digital twin ecosystem outputs in the illustrative HPT maintenance example.

Framework Step	Formal Construct Applied	Illustrative Output
State estimation	$y_{\text{hyb}}(t) = F(y_{\text{ph}}, y_{\text{dd}}, \omega)$	EGT margin $= 5.76 \pm 1.4$ °C, $Conf = 0.87$
RUL estimation	$RUL(t) = T_f(t) - t$	$RUL = 285$ FC, interval $210 - 360$ FC
Maintenance optimization	$p^*(t) = \arg\min J(p, t)$	p_1 selected, $J = 1.702$
Federated update	Validation gate and weighted aggregation	Update accepted, $w_k = 0.198$
Sustainability assessment	$J_{SM}(p, t)$	$J_{SM}(p_1) = 0.052$

This example demonstrates that the proposed framework can produce traceable and interpretable outputs when populated with concrete numerical values. The hybrid model provides a state estimate with uncertainty, the optimization function ranks maintenance alternatives, the federated update mechanism supports collaborative model improvement under data-governance constraints, and the sustainability objective links technical condition with lifecycle value and environmental trade-offs. Real-world applications would require calibrated physics-based models, validated AI/ML models, operational fleet datasets, risk functions derived from empirical or simulation-based evidence, and sustainability coefficients aligned with operator-specific reporting and governance requirements.

4. Discussion

4.1. Implications for Sustainable Aviation Transport Systems

The central implication of the proposed framework is that sustainable transport-system management can be strengthened by developing digital twins at the level of key operational assets. The aircraft digital twin contributes to sustainability through three main mechanisms. First, it enables emissions-aware management by linking aircraft condition, fuel consumption, operational profile, and environmental impact at the level of specific aircraft and missions. Second, it supports operational and resource efficiency by improving aircraft assignment, dispatch reliability, maintenance planning, spare-part preparation, and downtime reduction—interpreted broadly as efficient use of aircraft availability, maintenance resources, component life, and operational time. Third, it enables lifecycle optimization by preserving a continuous record of configuration, degradation, maintenance actions, and residual value, supporting evidence-based decisions about repair, replacement, modernization, reuse, recycling, and retirement.

These contributions are systemic rather than purely technical. When aggregated across a fleet, improved asset-level decisions influence fleet availability, disruption resilience, fuel efficiency, maintenance capacity, lifecycle cost, and emissions performance.

The multi-level relevance, from individual aircraft to fleet to transport-system sustainability, distinguishes the proposed framework from conventional monitoring or predictive maintenance approaches.

The sustainability management objective in Equation (1) should be interpreted as an asset-level decision-support construct rather than as a direct replication of industry-level sustainability reporting metrics. The ICAO Long-Term Aspirational Goal (LTAG) [2] and the IATA Fly Net Zero commitment [3] define the strategic direction of aviation decarbonization, especially the transition toward net-zero carbon emissions by 2050. However, these goals are normally formulated at the fleet, operator, sectoral, or policy level. The proposed aircraft digital twin ecosystem contributes at a different but complementary level: it provides aircraft-specific evidence about how technical condition, operational profile, maintenance actions, lifecycle extension, and resource use influence sustainability-relevant outcomes.

In this context, the terms of J_{SM} represent measurable evidence channels through which the digital twin can support sustainability-oriented planning. They do not exhaust the full scope of aviation sustainability, but they connect asset-level technical and lifecycle data with decisions that influence fuel efficiency, emissions, resource consumption, maintenance waste, lifecycle extension, and residual value (Table 6).

Table 6. Asset-level sustainability evidence provided by the aircraft digital twin ecosystem.

J_{SM} Term	Asset-Level Interpretation	Sustainability-Relevant Objective	Digital Twin Output
$Ems(t)$	CO_2 and other emissions associated with aircraft condition and mission profile	Emission-aware operation and support of net-zero trajectory assessment	Degradation-adjusted emissions estimate derived from aerodynamic, thermodynamic, and degradation models
$Fuel(t)$	Fuel consumption affected by aircraft configuration, engine condition, and operational profile	Fuel-efficiency improvement and reduction in degradation-induced fuel-burn penalties	Specific fuel consumption estimate as a function of technical state $S(t)$ and operational profile $O(t)$
$Res(t)$	Materials, spare parts, labour, and maintenance resources required over the planning horizon	Resource-efficient maintenance and lifecycle planning	Maintenance optimization output $p_m^*(t)$, including shop-visit frequency, part replacement volume, and resource allocation
$Waste(t)$	Maintenance waste, removed parts, and end-of-life component disposition	Circular economy support and reduction in unnecessary replacement	Lifecycle history $H(t)$, component condition at removal, reuse potential, and scrap/recycling indicators
$Life(t)$	Lifecycle extension benefits from condition-aware repair, maintenance, or modernization	Avoidance of premature retirement and support for lifecycle extension	RUL estimates, configuration tracking $C(t)$, and lifecycle transition analysis
$Value(t)$	Residual technical and economic value of the aircraft or component	Economic sustainability and fleet investment efficiency	Condition-based residual value trajectory and asset lifecycle management indicators

This mapping clarifies the sustainability role of the proposed framework. The strongest and most direct connection is provided by $Ems(t)$ and $Fuel(t)$, because aircraft condition, engine degradation, aerodynamic performance, and operational profile can be translated into fuel-burn and emissions estimates at the level of individual aircraft and missions. This asset-level granularity is important because degradation-induced fuel penalties are not uniform across a fleet; they depend on maintenance history, configuration state, operating environment, and mission profile.

The terms $Res(t)$ and $Waste(t)$ extend the sustainability logic beyond fuel and emissions. They allow maintenance planning to consider material use, shop-visit frequency, component replacement volume, and end-of-life disposition. This is particularly relevant for lifecycle-oriented digital twin ecosystems, where maintenance decisions influence not only short-term availability and cost, but also resource efficiency and circular economy outcomes.

The terms $Life(t)$ and $Value(t)$ capture lifecycle extension and residual value effects. A condition-aware decision to repair, restore, modernize, or continue operating an airworthy asset may defer premature replacement and preserve embodied technical and economic value. Conversely, excessive deferral may increase fuel burn, risk, or maintenance burden. The digital twin therefore supports explicit trade-off analysis between operational efficiency, lifecycle extension, residual value, emissions, and resource use.

The proposed framework does not claim to cover the full complexity of aviation sustainability governance. Sustainable aviation fuels, air traffic management efficiency, airport infrastructure, non-CO_2 climate effects, market-based measures, and regulatory enforcement mechanisms are outside the direct scope of the asset-level aircraft digital twin ecosystem. However, the framework provides an important technical and informational precondition for sustainability-oriented decision-making: an aircraft-specific evidence base linking degradation, maintenance, operation, resource use, and lifecycle value. This evidence can then be aggregated or coordinated at fleet, operator, and sectoral levels in support of broader ICAO LTAG and IATA Net Zero 2050 objectives.

The asset-level logic developed for aircraft is conceptually transferable to other transport modes. In railway systems, DTs for trains, locomotives, and track infrastructure can support condition-based maintenance, energy-efficient operation, timetable reliability, and infrastructure lifecycle renewal. In maritime transport, ship DTs support hull and engine monitoring, fuel optimization, emissions reporting, and end-of-life recycling. In road transport and urban mobility, DTs for buses, electric vehicle fleets, and infrastructure support maintenance planning, energy management, and emissions reduction.

The general decision-support structure

$$Asset\ Data \rightarrow DT\ Models \rightarrow Decision\ Views \rightarrow Planning\ Actions \\ \rightarrow Lifecycle\ Feedback$$

is applicable across modes. However, transferability does not imply direct replication: each transport mode has its own regulatory structure, data availability, lifecycle logic, degradation mechanisms, and stakeholder configuration. The proposed framework should be understood as a transferable systems logic rather than a universal technical template.

4.2. Cross-Case Mapping of Industrial Applications

The following case descriptions are based on publicly available industrial documentation and selected conference or academic sources. Therefore, the mapping should be interpreted as an analytical and illustrative comparison rather than as an operational audit or quantitative benchmarking of the platforms.

1. Lufthansa Technik AVIATAR

AVIATAR is a cloud-based platform integrating sensor data, maintenance records, telemetry, and environmental data to support component degradation monitoring, anomaly detection, and proactive maintenance scheduling [36,41,42]. Within the proposed framework, it primarily corresponds to the support and usage lifecycle phases and to maintenance planning decision outputs.

The case can be formalized as

$$D(t) \rightarrow \left\{M_{\text{dd}}(t), M_{\text{hyb}}(t)\right\} \rightarrow \left\{RUL_i(t), Pr_i^{\text{fail}}(t, \Delta T)\right\} \rightarrow P_m(t)$$

where $D(t)$ denotes the lifecycle data space, $M_{\text{dd}}(t)$ the data-driven model, $M_{\text{hyb}}(t)$ the hybrid model, $RUL_i(t)$ the remaining useful life of component i, $Pr_i^{\text{fail}}(t, \Delta T)$ the probability of failure of component i over the future interval ΔT, and $P_m(t)$ the maintenance planning output.

This mapping illustrates the maintenance objective introduced in the formal framework in operational form. A key limitation is that the capability is implemented within a specific platform boundary, constraining broader ecosystem potential.

2. Airbus Skywise

Skywise is a fleet-level data and analytics platform enabling cross-fleet learning, predictive and health monitoring, and pattern recognition across operators [37,43]. It corresponds to the multi-stakeholder model updating and federated learning logic of the proposed framework.

The mapping can be expressed as

$$\left\{D_k(t)\right\}_{k=1}^{K} \rightarrow M_G(t) \rightarrow \left\{V_k(t)\right\}_{k=1}^{K} \rightarrow \left\{A_k(t)\right\}_{k=1}^{K}$$

where $D_k(t)$ is the local dataset of stakeholder k, K is the number of participating stakeholders, $M_G(t)$ is the aggregated or shared global model, $V_k(t)$ denotes the stakeholder-specific decision view, and $A_k(t)$ represents the action or decision output generated for stakeholder k.

This structure indicates that an airline may use the platform for fleet availability management, while an OEM may extract aggregated reliability patterns, and maintenance organizations may prepare targeted interventions. The case demonstrates that cross-stakeholder value depends on data standardization, trust, access control, and governance.

3. GE Aerospace Maintenance Insight

GE Aerospace Maintenance Insight uses aircraft and component degradation information to support early detection, fleet health visualization, prioritization of maintenance issues, and corrective-action decision making [38]. Vibration, pressure, and temperature data are analyzed over multiple flight cycles to identify early signs of turbine blade degradation.

This case closely illustrates the hybrid modelling paradigm

$$y_{\text{hyb}}(t) = F[y_{\text{ph}}(t), y_{\text{dd}}(t), \omega(t)]$$

where $y_{\text{hyb}}(t)$ denotes the hybrid model output, $y_{\text{ph}}(t)$ the physics-based prediction, $y_{\text{dd}}(t)$ the data-driven prediction, and $\omega(t)$ the weighting or fusion parameter controlling the integration of the two model families.

In the context of engine lifecycle monitoring, this can be interpreted as

$$D_{\text{eng}}(t) \rightarrow \{M_{\text{therm}}(t), M_{\text{str}}(t), M_{\text{dd}}(t)\} \rightarrow \{HI(t), RUL(t), T_{\text{on-wing}}(t)\} \rightarrow P_{\text{eng}}(t)$$

where $D_{\text{eng}}(t)$ denotes engine-related operational and condition data, $M_{\text{therm}}(t)$ the thermodynamic model, $M_{\text{str}}(t)$ the structural model, $M_{\text{dd}}(t)$ the data-driven model, $HI(t)$ the health indicator, $RUL(t)$ the remaining useful life, $T_{\text{on-wing}}(t)$ the expected on-wing time and $P_{\text{eng}}(t)$ the engine maintenance or lifecycle planning output.

The case demonstrates that the most mature aviation digital twin applications still operate predominantly at the subsystem level. The proposed framework extends this logic to aircraft-level lifecycle ecosystems.

4. Rolls-Royce and Microsoft Azure

Rolls-Royce digital twin and Intelligent Engine applications connect engine data, advanced analytics, cloud infrastructure, and individualized maintenance recommendations to support engine lifecycle management, maintenance planning, efficiency improvement, and emissions-oriented decision support [39,40]. Predictive analytics are used to pre-order parts and assign technicians based on expected fault profiles.

The mapping can be represented as

$$D_{\text{engine}}(t) \rightarrow M_{\text{deg}}(t) \rightarrow \{Workscope(t), SpareParts(t), Resources(t)\} \rightarrow A_{\text{MRO}}(t)$$

where $D_{\text{engine}}(t)$ denotes engine data, $M_{\text{deg}}(t)$ the degradation model, $Workscope(t)$ the maintenance workscope, $SpareParts(t)$ the spare-parts requirement, $Resources(t)$ the required maintenance resources, and $A_{\text{MRO}}(t)$ the MRO action plan.

More generally, this case may be interpreted as a transition from predictive analytics to prescriptive maintenance planning:

$$D_{\text{engine}}(t) \rightarrow \hat{S}_{\text{engine}}(t + \Delta T) \rightarrow P^{*}_{\text{MRO}}(t) \rightarrow A_{\text{MRO}}(t)$$

where $\hat{S}_{\text{engine}}(t + \Delta T)$ is the predicted future engine state over the planning horizon ΔT, $P^{*}_{\text{MRO}}(t)$ is the optimized MRO plan and $A_{\text{MRO}}(t)$ denotes the resulting maintenance action. The case reinforces the architectural importance of the data pipeline and cloud infrastructure for distributed MRO coordination.

5. Cross-Case Comparison and Framework Gaps

To compare the four industrial cases in a transparent and analytically consistent manner, a scoring logic was defined across six framework dimensions derived from the formal and architectural constructs developed in Section 3. The purpose of this scoring is not to provide a quantitative benchmark of platform performance, but to structure the interpretive case mapping and make the basis of comparison explicit. The scores reflect the degree to which publicly documented platform capabilities correspond to the dimensions of the proposed aircraft digital twin ecosystem framework. The consolidated scores are then used to construct the radar comparison.

All dimensions were evaluated using a unified five-point ordinal scale: 1 = absent or not documented; 2 = emerging or partially described capability; 3 = established operational capability; 4 = advanced and integrated capability; and 5 = leading capability with broad ecosystem-level integration. The scores are based only on publicly available sources, including official platform documentation, peer-reviewed publications, and conference papers cited in references [36–44]. Therefore, they should be interpreted as documented maturity scores rather than as a complete assessment of proprietary or internal platform capabilities.

The six dimensions are defined as follows. Lifecycle coverage reflects the extent to which the platform supports digital twin functions across aircraft lifecycle phases, including operation, MRO, modernization, lifecycle extension, and end-of-life considerations. Modelling depth evaluates the sophistication and diversity of the model set, including rule-based monitoring, data-driven models, physics-based models, hybrid modelling, uncertainty treatment, and parameter updating. Stakeholder integration captures the breadth of stakeholder-specific views and the degree to which airlines, MRO providers, OEMs, regulators, airports, or service partners are connected through shared data or decision environments. Decision-support breadth reflects the number and diversity of decision-support scenarios supported by the platform, such as maintenance optimization, operational efficiency, safety and risk management, lifecycle planning, economic performance, regulatory compliance, training, and sustainability. Sustainability capability evaluates whether the platform links technical condition to fuel consumption, emissions, resource use, lifecycle extension, residual value, or other sustainability-related indicators. Federated governance reflects the presence of distributed data access, controlled model updating, validation gates, access-control rules, auditability, and multi-stakeholder governance mechanisms.

Table 7 summarizes the consolidated scores. The scores should be read as structured qualitative assessments rather than interval-scale measurements. A score of 4 does not imply twice the capability of a score of 2; instead, it indicates a higher documented level of maturity on the corresponding dimension.

Table 7. The consolidated scores used to construct the radar chart.

Framework Dimension	Definition	AVIATAR	Airbus Skywise	GE Maintenance Insight	Rolls-Royce/Azure	Proposed Framework/Reference Profile
Lifecycle coverage	Coverage of lifecycle phases from operation and MRO toward broader lifecycle management	3	3	2	3	5
Modelling depth	Diversity and integration of model types, including data-driven, physics-based, hybrid, and uncertainty-aware models	4	3	4	5	5
Stakeholder integration	Breadth of stakeholder-specific views and cross-organizational data or decision flows	2	4	2	3	5
Decision-support breadth	Diversity of supported decision scenarios across maintenance, operations, safety, lifecycle, economic, regulatory, training, and sustainability domains	3	4	3	4	5
Sustainability capability	Integration of fuel, emissions, resource, lifecycle-extension, or residual-value indicators into decision support	2	2	2	3	5
Federated governance	Support for distributed data access, controlled model updating, validation, auditability, and governance mechanisms	2	3	1	2	5
Mean score	Compact descriptive profile indicator; not used as a ranking criterion	2.7	3.2	2.3	3.3	5.0

To make the comparison more explicit, the proposed framework is also shown as a reference profile across the same six dimensions. This profile should not be interpreted as an empirical maturity score of an implemented industrial platform. Rather, it represents the intended target capability profile of the conceptual aircraft digital twin ecosystem developed in this paper. Since the six dimensions are derived from the framework itself, the proposed framework receives the maximum reference value on each dimension. This reference profile is used only as a benchmark for interpreting gaps between current industrial practice and the proposed lifecycle-oriented ecosystem model.

Accordingly, Table 7 includes the proposed framework as a "reference target" profile. The comparison shows that current industrial cases demonstrate strong capabilities in selected areas, especially predictive maintenance, modelling depth, and fleet analytics, but remain less developed in full lifecycle coverage, sustainability-oriented lifecycle trade-offs, and federated governance. The proposed framework is therefore not presented as a competing industrial platform, but as an integrative target model that clarifies which additional capabilities would be required for aircraft digital twins to support lifecycle planning and sustainable aviation transport management at the ecosystem level.

Based on these consolidated scores, Figure 9 visualizes the comparative profiles of the four cases across the six framework dimensions.

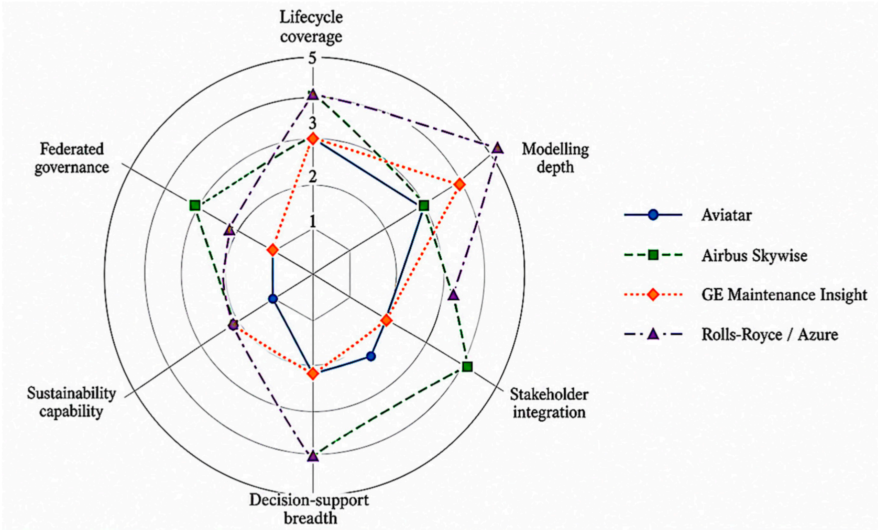

Figure 9. Radar comparison of four representative industrial cases across six framework dimensions.

The outer reference profile of the proposed framework indicates the conceptual target state defined by the lifecycle-oriented aircraft digital twin ecosystem. The gap between this reference profile and the industrial case profiles should be interpreted as a framework-alignment gap rather than as a direct performance deficit. In particular, the comparison highlights that existing platforms already provide mature capabilities in predictive analytics and maintenance-oriented modelling, whereas ecosystem-level lifecycle governance, sustainability trade-off analysis, and federated model updating remain less consistently documented.

The radar representation shows that the cases differ not only in technical maturity but also in their alignment with the proposed lifecycle-oriented ecosystem framework. Aviatar is strongest in predictive maintenance and maintenance-oriented decision support. Airbus Skywise demonstrates broader stakeholder and fleet-level data integration. GE Maintenance Insight is particularly relevant for engine lifecycle analytics and remaining useful life estimation. Rolls-Royce/Azure shows strong modelling depth and cloud-enabled MRO optimization. At the same time, the comparison indicates that sustainability capability and federated governance remain comparatively underdeveloped across most current industrial implementations.

The consolidated scores should be interpreted as an illustrative framework-alignment analysis rather than as a comprehensive benchmarking assessment or performance ranking of the selected platforms. The scores are based on publicly documented capabilities and may not reflect proprietary internal functions or platform-specific implementation strategies. Consequently, a lower score in a given dimension does not necessarily indicate a technological limitation; it may reflect stakeholder priorities, business requirements, intellectual property protection, regulatory constraints, or the deliberate strategic focus of the platform. The purpose of the comparison is therefore to identify visible alignment and gaps relative to the proposed lifecycle-oriented aircraft digital twin ecosystem, rather than to evaluate the overall maturity or adequacy of individual industrial solutions.

The cross-case analysis confirms that industrial practice is moving in the same direction as the proposed framework, but often in segmented form. Current implementations are strongest in predictive maintenance, fleet analytics, engine health monitoring, and component-level lifecycle management, while full aircraft-level lifecycle governance, sustainability trade-off analysis, and federated model validation remain less developed.

The common decision-support chain can be expressed as

$$D(t) \to M(t) \to P(t) \to V_k(t) \to A_k(t) \to D(t+1)$$

where $D(t)$ denotes the lifecycle data space, $M(t)$ the model set, $P(t)$ the planning and management outputs,$V_k(t)$ the stakeholder-specific view for stakeholder k, $A_k(t)$ the corresponding stakeholder action, and $D(t+1)$ the updated lifecycle data space after the action has been implemented and observed.

This chain is present in all four cases, although different cases are strongest in different links of the chain. AVIATAR is strongest in the transition from operational data to maintenance planning. Skywise is strongest in multi-stakeholder data aggregation and fleet-level decision views. GE Maintenance Insight is strongest in a hybrid model-based engine health assessment. Rolls-Royce/Azure is strongest in the transition from predictive engine analytics to prescriptive MRO planning. Thus, the case mapping supports the relevance of the proposed framework while also identifying the remaining gap between current industrial implementations and a fully integrated aircraft digital twin ecosystem.

Cross-referencing the radar chart scores with the five-level maturity model defined in Table 6 reveals that all four platforms operate at Level 3 (Predictive) or at the boundary between Levels 3 and 4 (Prescriptive). The primary bottleneck preventing progression to Level 4 is consistently the federated governance dimension (FG $\leq$ 3 for all cases), while the sustainability capability dimension (SC $\leq$ 3) represents a secondary constraint. No platform in the current landscape reaches Level 5 (Adaptive), confirming that the fully federated, sustainability-integrated digital twin ecosystem proposed in Section 3 represents a forward-looking target architecture rather than a description of current operational practice. This finding provides an empirically grounded anchor for the maturity model and defines a measurable gap between the present industrial state and the framework's normative vision.

4.3. Limitations and Future Research Directions

Several limitations should be acknowledged. First, the study is conceptual and framework-oriented; the framework has not been implemented as a full-scale operational DT using real airline, MRO, OEM, or regulatory datasets. Second, the mathematical framework is intentionally generic and requires instantiation for specific aircraft systems, sensor configurations, and operational contexts. Third, the framework assumes sufficiently reliable lifecycle data, whereas in practice, aviation data are fragmented across organizations and differ in quality, completeness, and certification status. Fourth, multi-stakeholder coordination requires trust, secure protocols, validation procedures, access-control policies, and accountability rules not yet fully specified. Fifth, sustainability indicators are treated conceptually.

Future research should proceed in four main directions. Empirical instantiation should apply the framework to selected aircraft subsystems or fleet datasets to test computational feasibility and decision-support value. Model validation should include verification of physics-based models and trustworthiness assessment of AI/ML and federated models in operational environments. Sustainability quantification should develop measurable lifecycle metrics connecting DT outputs to environmental, economic, and resource-efficiency indicators. Governance integration should embed DT recommendations into maintenance approval, fleet management, regulatory compliance, and lifecycle decision-making work-

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flows. Additionally, mode-specific adaptation of the framework for railway, maritime, and road transport domains should be investigated to determine which elements are generic and which are aviation-specific.

5. Conclusions

This paper proposed a lifecycle-oriented aircraft digital twin ecosystem framework for sustainable aviation transport systems. The main argument is that an aircraft digital twin should not be treated only as a virtual representation for monitoring or predictive maintenance, but as an asset-level information, modelling, and decision-support ecosystem that connects aircraft condition, lifecycle data, stakeholder responsibilities, and planning decisions.

The proposed framework integrates physics-based, data-driven, hybrid, probabilistic, and federated modelling approaches within a multi-layer architecture. The formal framework describes the aircraft as a lifecycle-evolving system-of-interest and the corresponding digital twin as a dynamic set of models, data, parameters, stakeholder views, and planning outputs. It formalizes lifecycle transitions, hybrid modelling, federated model updating, validation gates, maintenance and operational optimization, and sustainability-oriented decision objectives. In this way, the framework connects technical aircraft condition with planning and management decisions across the lifecycle.

A key contribution of the study is the inclusion of federated learning and governance as essential elements of aircraft digital twin ecosystems. This is important because aviation data are distributed across multiple organizations and are often proprietary, safety-critical, regulated, and commercially sensitive. The proposed federated logic enables local model training, validation of updates, global aggregation, and redistribution of improved models without requiring full centralization of raw data.

The industrial case mapping shows that several elements of the proposed framework already exist in current aviation digitalization practice. Platforms such as AVIATAR, Airbus Skywise, GE Aerospace Maintenance Insight, and Rolls-Royce/Azure-based digital twin applications demonstrate progress in predictive maintenance, fleet analytics, hybrid engine modelling, and cloud-enabled MRO optimization. However, these implementations remain fragmented. Full aircraft-level lifecycle governance, sustainability trade-off analysis, federated validation, and multi-stakeholder decision orchestration are still insufficiently developed.

The study is conceptual and should be interpreted as a systems-level reference model rather than as a fully implemented operational platform. Future research should focus on empirical testing with real aircraft, fleet, MRO, or subsystem datasets; quantitative validation of physics-based, AI/ML, hybrid, and federated models; measurable sustainability indicators; and integration of digital twin recommendations into regulated maintenance, compliance, and lifecycle-governance workflows.

The paper demonstrates that aircraft digital twin ecosystems can support sustainable aviation transport systems when designed not only for technical monitoring but also for lifecycle planning, multi-stakeholder governance, and evidence-based decision support.

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Appendix A

Appendix A.1. Purpose of the Traceability Check

To strengthen the internal consistency of the framework-development process, a construct traceability check was applied. The purpose of this check was to verify that the principal formal constructs introduced in Section 3 are not isolated mathematical expressions but are linked to: (i) a conceptual origin in the reviewed literature; (ii) a corresponding formal element in the proposed aircraft digital twin ecosystem framework; and (iii) a planning, management, validation, or governance output.

This traceability logic supports the four-stage synthesis described in Section 2: classification, conceptual synthesis, formalization, and interpretive structuring. In this sense, the traceability matrix does not provide empirical validation of the framework, but it improves the transparency of the conceptual design process by showing how the main framework elements move from source concepts to formal constructs and then to decision-support functions.

Appendix A.2. Construct Traceability Matrix

Table A1. Construct traceability matrix: from source concept to formal framework element and decision-support output.

Source Concept	Representative References	Formal Construct in Section 3	Decision-Support or Governance Output
Digital twin as a dynamic virtual representation	[8–11]	$DT_A(t) = \{M(t), D(t), \Theta(t), V(t), P(t)\}$	Lifecycle state tracking; planning and management outputs $P(t)$
Aircraft as lifecycle-evolving system of interest	[5,6,16,17]	$A(t) = \{C(t), S(t), O(t), E(t), H(t)\}$	Configuration tracking, technical-state monitoring, lifecycle-history representation
Aircraft lifecycle phases	[5,6,16,17]	$L = \{L_{\text{des}}, L_{\text{man}}, L_{\text{ops}}, L_{\text{mro}}, L_{\text{mod}}, L_{\text{eol}}\}$; transition operator Φ_i	Lifecycle-phase-specific decision views; transition from design intent to as-built, as-operated, maintained, modified, and end-of-life states
Physics-based engine and structural modelling	[18–22,24–27]	$y_{\text{ph}}(t) = f_{\text{ph}}(x(t), u(t), \theta_{\text{ph}}, \xi(t))$; model set $\{M_{\text{str}}, M_{\text{aero}}, M_{\text{sys}}, M_{\text{therm}}\}$	Structural integrity assessment; performance monitoring; explainable engineering assessment
Data-driven anomaly detection and RUL estimation	[18–23,33]	$y_{\text{dd}}(t) = g(D(t), \theta_{\text{dd}})$; $RUL(t) = T_f(t) - t$	Predictive maintenance schedules; anomaly indicators; failure probability estimation
Hybrid physics–data model integration	[24–26,33–35]	$y_{\text{hyb}}(t) = F(y_{\text{ph}}(t), y_{\text{dd}}(t), \omega(t))$	Health indicators; degradation tracking; on-wing time estimation; improved model robustness
Lifecycle data space	[6,13,14]	$D(t) = \{D_{\text{sens}}(t), D_{\text{ops}}(t), D_{\text{mro}}(t), D_{\text{env}}(t), D_{\text{conf}}(t)\}$	Integrated use of sensor, operational, maintenance, environmental, and configuration data
Multi-stakeholder aviation data environments	[13,14,36–44]	Stakeholder views $V_k(t)$; stakeholder actions $A_k(t)$	Role-specific decision outputs for airlines, MRO providers, OEMs, regulators, airports, and service partners
Lifecycle governance and auditability	[5,13,14,16,17]	$\text{GOV} = \{R_{\text{data}}, R_{\text{access}}, R_{\text{model}}, R_{\text{valid}}, R_{\text{audit}}\}$	Controlled data sharing, access management, model-update authority, validation rules, and traceability
Federated learning for distributed model updating	[12,13]	$\theta_G(t+1) = \sum_{k=1}^{K} w_k(t)\theta_k(t+1)$; validation gate conditions	Fleet-wide model improvement without raw-data centralization; controlled multi-stakeholder learning
Validation and trustworthiness	[5,12–14,16,17]	$e_{\text{val}}(t) = \| y_{\text{real}}(t) - y_{\text{DT}}(t) \| \le \varepsilon_{\text{val}}$; drift and rollback conditions	Model credibility, AI/ML trustworthiness, system assurance, safe rollback of degraded model updates
Condition-based and predictive maintenance optimization	[6,7,13,14]	$p_m^*(t) = \arg\min_{p_m \in P_m} J_m(p_m, t)$	Inspection plans, workscope optimization, spare-part pre-positioning, risk-based maintenance decisions
Operational optimization	[6,13,14]	$p_o^*(t) = \arg\max_{p_o \in P_o} [\cdots]$	Route assignment, fleet allocation, fuel-loading support, and dispatch reliability indicators
Sustainability objectives in transport planning	[1–3,15]	$J_{SM}(SM, t) = c_1 Ems + c_2 Fuel + c_3 Res + c_4 Waste - c_5 Life - c_6 Value$	Eco-efficient operations, emissions-aware planning, lifecycle extension, residual-value preservation, end-of-life decisions
Digital twin maturity and adoption progression	[13,14]	Five-level maturity model: Monitoring → Diagnostic → Predictive → Prescriptive → Adaptive	Evidence-based capability roadmap for aircraft digital twin ecosystem adoption

Appendix A.3. Interpretation of the Traceability Matrix

The matrix shows that the proposed framework is constructed through a sequence of concept-to-function transformations. General digital twin concepts are translated into the aircraft-specific construct $DT_A(t)$, while aircraft lifecycle and systems-engineering concepts are represented through the lifecycle set L, aircraft state representation $A(t)$, and transition operator Φ_i. Aviation-specific modelling streams, including physics-based, data-driven, and hybrid approaches, provide the basis for the model set $M(t)$, state-estimation functions, RUL estimation, and maintenance optimization logic.

The multi-stakeholder character of aviation is represented through stakeholder-specific views $V_k(t)$, stakeholder actions $A_k(t)$, and the governance structure GOV. Federated learning is included because centralized data integration is often impractical in aviation contexts where data are proprietary, safety-critical, commercially sensitive, and regulated. Sustainability constructs are connected to transport-system objectives by linking aircraft condition, fuel consumption, emissions, resource use, lifecycle extension, and residual value within a common decision-support function.

Thus, the traceability matrix supports the internal coherence of the proposed framework. Each major construct has both a conceptual origin and a decision-support role. This does not imply empirical validation, but it demonstrates that the formal framework is systematically derived rather than assembled as a set of unrelated mathematical expressions.

Appendix A.4. Framework Boundary Definition and Excluded Concepts

The framework-development process also involved the consideration of several related concepts that were not adopted as separate framework components. These exclusions were not omissions, but boundary-setting decisions intended to keep the framework at the level of a systems-oriented reference model.

Blockchain mechanisms were considered as a possible means of ensuring traceability and auditability of model updates across stakeholders. However, blockchain was not included as a separate framework component because its main contribution is implementation-specific immutable transaction logging. In the proposed framework, auditability is represented at the architectural level through R_{audit} within the governance structure GOV. Blockchain may therefore be used in future implementations, but it is not required as a defining element of the conceptual architecture.

Agent-based modelling was considered as a possible method for simulating interactions among airlines, MRO providers, OEMs, regulators, airports, and service partners. It was not included because the objective of the paper is to develop a lifecycle-oriented aircraft digital twin ecosystem framework, not to simulate emergent behavioural dynamics among autonomous stakeholders. Stakeholder-specific views $V_k(t)$, actions $A_k(t)$, and governance rules provide sufficient representational depth for the planning and management focus of the study.

Digital thread concepts from product lifecycle management and manufacturing informatics were reviewed as a possible basis for representing lifecycle continuity. The substance of digital thread logic is incorporated in the framework through lifecycle data $D(t)$, configuration state $C(t)$, and transition operator Φ_i, and the as-built baseline DT_A^0. However, the term "digital thread" is not adopted as a central construct in order to avoid conflating the aircraft digital twin ecosystem framework with manufacturing-specific terminology.

Blockchain, agent-based modelling, and digital thread concepts may be relevant in future extensions of the framework, particularly when the proposed architecture is implemented in operational environments. In the present study, however, they are treated as optional implementation or extension mechanisms rather than as core elements of the proposed aircraft digital twin ecosystem.

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Appendix A.5. Limitations of the Traceability Check

The traceability matrix provides an internal consistency check, not an external validation of the proposed framework. It relies on the literature and industrial sources reviewed in the paper and therefore reflects the conceptual and documentary basis of the study. The matrix also focuses on principal constructs rather than every possible modelling detail. Future empirical work should further test whether these constructs remain adequate when the framework is instantiated using real aircraft, fleet, MRO, OEM, or regulatory datasets.

Nevertheless, the traceability check strengthens the methodological transparency of the study by clarifying how the framework elements are derived, how they relate to one another, and how they support the planning, management, validation, governance, and sustainability objectives of the proposed aircraft digital twin ecosystem.

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