A System of Systems Architecture for Optimizing Aircraft Health Management in Civil Aviation

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ABSTRACT

This study proposes a system of systems (SoS) architecture for efficient aircraft health management (AHM) in civil aviation from the perspective of an aircraft manufacturer and formulates AHM as a multi-objective optimization problem. First, the SoS architecture is described to capture the interrelationship of the strategic capabilities required among the relevant stakeholders including airline customers, and the regulatory authority by using the Unified Architecture Framework (UAF). Parameters to measure strategic capabilities and operational activities are identified and the relationships between them are defined using parametric causal correlation. Next, AHM performance, effect, and amount of required data are formulated in terms of the identified variables in the SoS architecture description. Quantification enables the maximization of the effectiveness of AHM implementation by formulating it as a multi objective optimization problem, which allows for the quantitative assessment of the relationships between the context of AHM implementation and strategic capabilities. This formulation makes it possible to evaluate AHM effectiveness quantitatively, improving upon our previously proposed SoS architecture model, which only evaluated the relationship between stakeholders qualitatively.

1. INTRODUCTION

Civil aviation passenger demand is predicted to approximately double over the next 20 years (Japan Aircraft Development Corporation [JADC], 2024.). Meanwhile, the domestic shortage of mechanics in Japan has been forecasted as a critical challenge (Ministry of Land, Infrastructure, Transport and Tourism, 2025). To address the mechanics shortage and accommodate future increases in aviation passenger demand, enhancing the efficiency of civil aircraft maintenance is essential. This requires improving the efficiency of maintenance planning through the implementation of Aircraft Health Monitoring (AHM) (International Aircraft Development Fund [IADF], 2014), including predictive maintenance capabilities. For instance, according to an IATA report (IATA, 2023), AHM implementation could reduce annual operational costs by over $3 billion. Additionally, operational and maintenance DX is positioned as part of JAXA's aircraft lifecycle DX technology, with a vision that by 2050, predictive maintenance will be conducted systematically and efficiently for all systems, and scheduled maintenance will be optimized (Aoyama, Mizobuchi, & Hashimoto, 2024).

However, AHM adoption in civil aviation remains limited due to challenges including prediction complexity, safety and certification issues, implementation costs, impact estimation difficulties, and data availability and quality concerns (Teubert, Pohya, & Gorospe, 2023.).

Numerous studies on AHM have been reported. In data-driven aerospace engineering (Brunton, Nathan, Manohar, Aravkin, Morgansenet al., 2021), it is proposed that effective utilization of data provides significant opportunities for improvement and optimization of aircraft maintenance. AHM is classified into data-driven, model-based, and knowledge-based types (Kordestani, Orchard, Khorasani, & Saif, 2023), and it has been shown that technical challenges such as real-time implementation, uncertainty management, and system-level prediction remain.

Regarding economic evaluation, reports have been made on methods that enable optimization including multifaceted objectives such as environmental burden in addition to conventional economic indicators, using the case of an A320 tire pressure monitoring system (Meissner, Meyer & Wicke, 2021). According to this, AHM implementation can achieve significant cost reduction and realize substantial reduction in environmental burden. On the other hand, it has also been shown that high error rates in failure prediction may cause deterioration in the lifecycle cost-effectiveness of AHM (Hölzel & Gollnick, 2015).

Regarding AHM system design, the necessity of being user requirement-driven rather than enabling technology or solution technology-driven has been shown (Hu, Miao, Si, Pan & Zio, 2022). Systems engineering approaches have been applied to AHM design, revealing that effective PHM systems depend on the integration of both functional and physical architectures (Kunche, Chen, & Pecht, 2012). These studies focus on "detection" and "analysis" among AHM functions. However, since AHM includes comprehensive functions of "sense", "acquisition", "transfer," "analysis", and "action" (IATA, 2023) and is a complex system involving multiple stakeholders, it is considered effective to comprehensively evaluate AHM through integrated analysis using a System of Systems (SoS) approach.

SoS architecture can be described using UAF (Unified Architecture Framework) (The Object Management Group [OMG], 2022). Regarding describing maintenance as architecture, practical examples of applying UAF to examine the compatibility between tactical needs and maintenance capabilities in military aviation have been reported (Olsson, Funk, Candell, Sohlberg, & Karim, 2021). It has also been reported that applying UAF to maintenance planning for offshore oil and gas systems can achieve risk visualization, improved traceability, and effective information exchange (Jensen, Dan, Kihlström, Altamiranda, & Hause, 2024).

Regarding the application of system dynamics methodology (Sterman, 2000), causal relationship analysis using this method has been conducted for repair costs of aviation equipment, showing that reliability improvement through failure rate reduction is the most effective cost reduction measure (Liu, & Huang, 2015). Furthermore, there are examples where conventional preventive maintenance and condition-based maintenance (CBM) in aircraft maintenance were compared and analyzed using system dynamics models, showing that CBM implementation reduces unplanned removals and improves aircraft availability (Hussain, Burrow, Henson & Keogh, 2016).

Regarding aircraft maintenance optimization, a theoretical foundation is proposed to optimize strategy for multi-stage maintenance of aircraft structures and the possibility of advanced maintenance through integration with Structural Health Monitoring (SHM) systems was demonstrated (Ito, 2013). In scheduling optimization, Sriram and Haghani (2003) formulated maintenance scheduling and aircraft reassignment as an integrated mixed-integer programming problem, demonstrating practical solutions for heterogeneous aircraft fleets. In military aviation, Verhoeff et al. (2015) developed a model that maximizes operational readiness by integrating availability, serviceability, and sustainability considerations.

Recent advances focus on predictive maintenance technology integration. Wang et al. (2024) proposed a real-time maintenance framework based on Remaining Useful Life (RUL) prediction, while Vianna and Yoneyama (2018) achieved significant cost reductions in redundant systems. Rodrigues et al. (2015) enabled efficient maintenance planning considering system-wide interdependencies through their S-RUL approach, which integrates PHM systems with system architecture information. These research trends demonstrate evolution from theoretical foundations to practical implementation, from single-objective to multi-objective approaches, from component-level to system integration, and from scheduled to predictive maintenance, indicating that aircraft maintenance is evolving into a strategic operational management system.

However, there are no examples of systematically optimizing AHM implementation in commercial aircraft by combining SoS architecture description and system dynamics.

To structurally address these complex AHM-related issues, the authors previously proposed a method for analyzing AHM implementation context by describing it as a SoS architecture involving passengers, airlines, aircraft manufacturers (OEMs: Original Equipment Manufacturers), certification authorities, and suppliers as stakeholders, and evaluating implementation effectiveness (Koizumi, & Kogiso, 2024a). The authors also evaluated AHM implementation effects by focusing on trade-offs between Measures of Effectiveness (MoE) among elements constituting the SoS architecture for civil passenger aircraft maintenance including AHM (Koizumi, & Kogiso, 2024b).

This paper utilizes these research findings to address the structural problems affecting AHM implementation progress. Civil aviation maintenance AHM implementation is conceptualized as an SoS architecture involving passengers, airlines, OEMs, maintenance repair and operations providers (MROs), and regulatory authorities as stakeholders, evaluating how AHM implementation affects stakeholder objectives. Airline and OEM strategy and operations views are described using the UAF, and structural causal relationships are extracted in the form of causal loop diagrams using system dynamics methodology. Based on this framework, the effects of AHM implementation on stakeholders are formulated as MoE interrelationships. Using these formulations, two AHM operational patterns are comparatively evaluated using Delta Air Lines' 2023 data from the publicly available U.S. DOT Form 41(U.S. Department of Transportation [U.S. DOT], 2024), which the U.S. Department of Transportation requires American airlines to report. Subsequently, multi-objective optimization of AHM adoption rates is performed with the objective of maximizing airline benefit through AHM by maximizing operational reliability and maintenance technician reduction rates, while minimizing the data communication volume required for AHM implementation.

2. SOS ARCHITECTURE OF AHM IN CIVIL AVIATION

The scope of this SoS architecture addresses AHM implementation in civil aircraft maintenance. In this context, an OEM serves multiple airlines as customers and provides AHM as a solution to improve aircraft operations and maintenance efficiency by utilizing aircraft and airline information. It is projected that aviation passenger demand will double from the present to the future, while maintenance technician candidates are expected to decrease in Japan. Under this scenario, the strategies that OEMs and airlines should adopt and how they can improve operations through AHM implementation are described.

UAF provides an appropriate framework for SoS architecture description (Martin, 2025). UAF is an integrated architecture framework that complies with ISO/EC/IEEE 42010:2011 "Systems and Software Engineering - Architecture Description" (International Standards Organization [ISO], 2011) and is applicable to SoS description in both military and civilian contexts. This research references UAF's domain metamodel (OMG, 2022) that defines UAF framework and element relationships but does not employ UAF Modeling Language (UAFML) provided as UAF's description language. For the SoS architecture description, the structure creation tool Balus (Levii Inc., 2023) (Miura, & Sakamoto, 2023), provided by Levii Corporation was utilized.

2.1. Ontology of SoS Architecture

Elements used for the views are selected from UAF's domain metamodel to capture stakeholder concerns. The causal loop view is used in addition to the views defined by UAF. Causal loops are defined in system dynamics methodology as a method for describing correlational relationships between parameters. A method (Koizumi, Morino, Hara & Aoyama, 2025) that combines UAF views with causal loop views from system dynamics is employed. This research describes the SoS Architecture using three views: (1) strategic view, (2) operational view, and (3) causal loop view. The elements used for the views and the relationships between elements (ontology of SoS description) are shown in Figure 1.

(1) Strategic motivation and goal view: Describes the capabilities which are required to achieve goals in a certain phase, linking them with drivers as motivation. Furthermore, it describes how effects brought about by capabilities ultimately lead to outcomes.

(2) Stakeholder context view: Describes the stakeholders and the exchange items between them.

(3) Operational process view: Describes the operational activities among stakeholders and the exchange items between activities.

Table 1. Stakeholder Concerns

Type	Concern
Social	As aviation demand is expected to double over 20 years, securing adequate aviation transportation capacity is essential.
Airline	While aviation demand presents a favorable business opportunity, expanding transportation capacity through cost-effective methods (including AHM) with high return on investment is desired.
	Implementing measures to address mechanic shortage (including AHM) is also necessary
OEM	Although airline aircraft demand expansion represents a positive business opportunity, avoiding increased aircraft manufacturing fixed costs is preferred.
	Monetizing new service opportunities (including AHM) associated with increased flight hours is also sought.

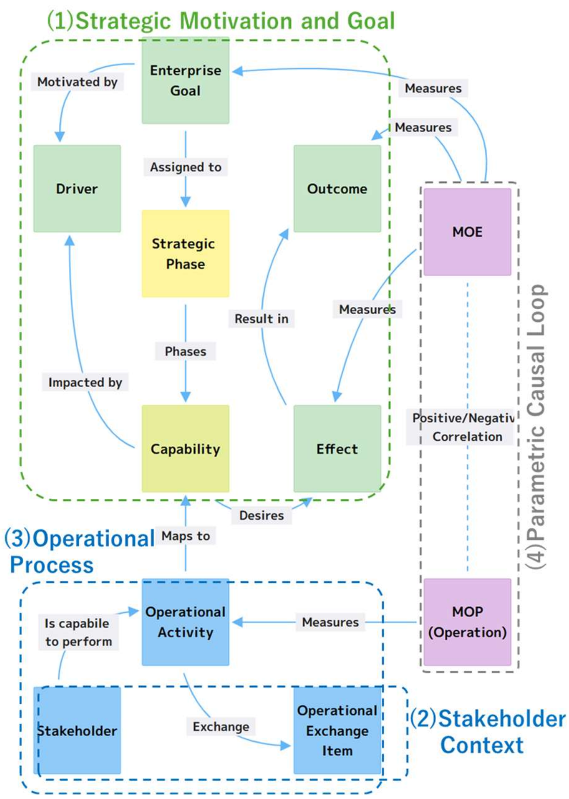

Figure 1. Ontology of SoS Architecture Description

(4) Parametric causal loop view: Describes major causal relationships of MoE brought about by capabilities, and shows the relationship with MoP (Measure of Performance) that measures operational results. The system dynamics methodology is applied for describing causal loops.

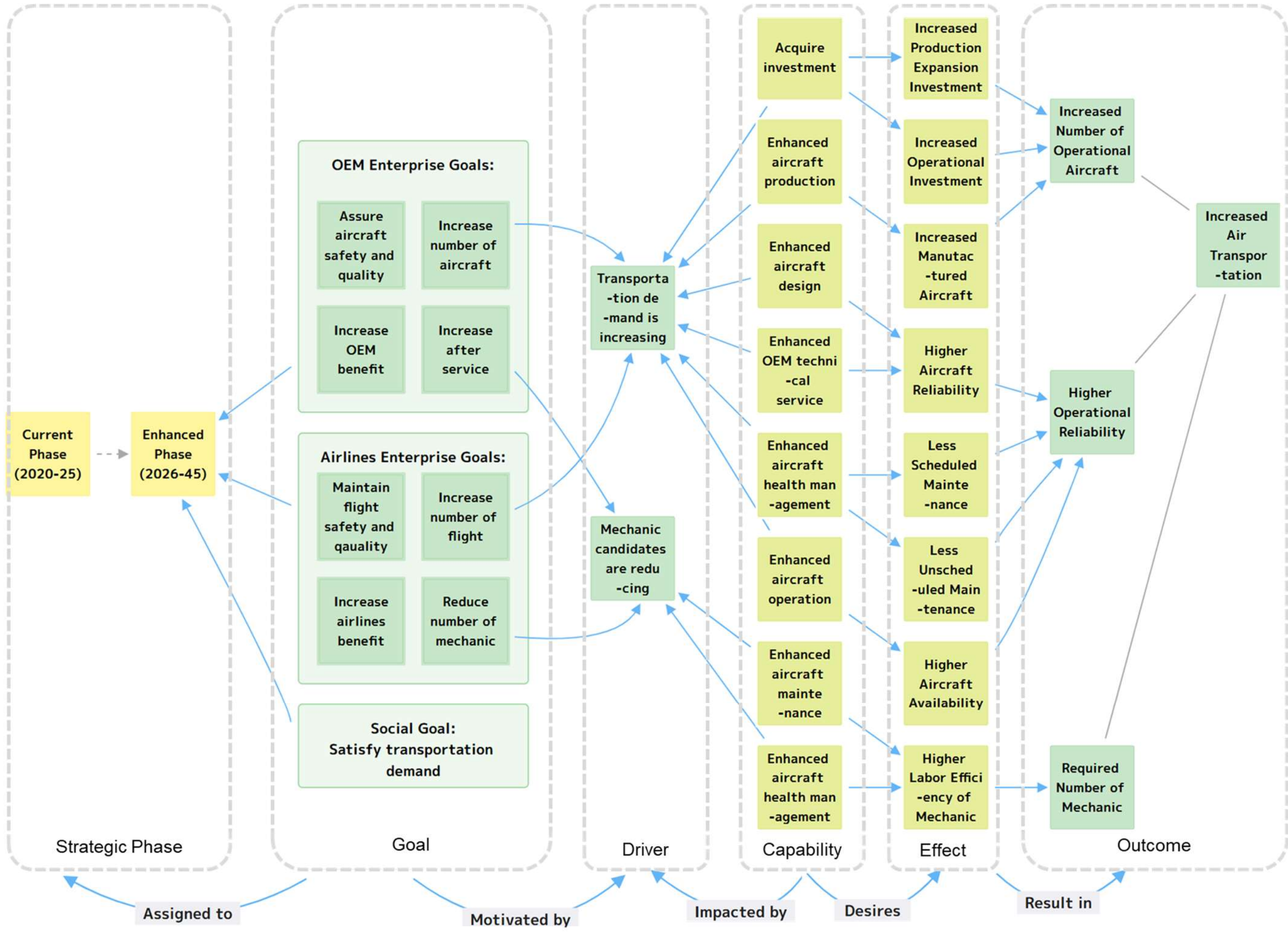

Figure 2. View (1) Strategic Motivation and Goal View

The SoS architecture is described to capture stakeholder concerns which are shown in Table 1. Based on the architectural description from strategic and operational viewpoints, major causal relationships between parameters constituting the architecture are defined in the causal loop view. Next, the causal relationships of parameters through the causal loop view are formulated. Using the formulated results, the architecture is evaluated, and the major parameters of the architecture are multi-objective optimized.

2.2. Strategic Motivation and Goal View

Figure 2 shows the OEM, airline, and social strategic motivations and goals using View (1). It describes that while the OEM and airlines have different respective goals, they share the common social goal of satisfying passenger demand that will double by 2045. The OEM aims to ensure aircraft safety and quality, increase aircraft production numbers, and

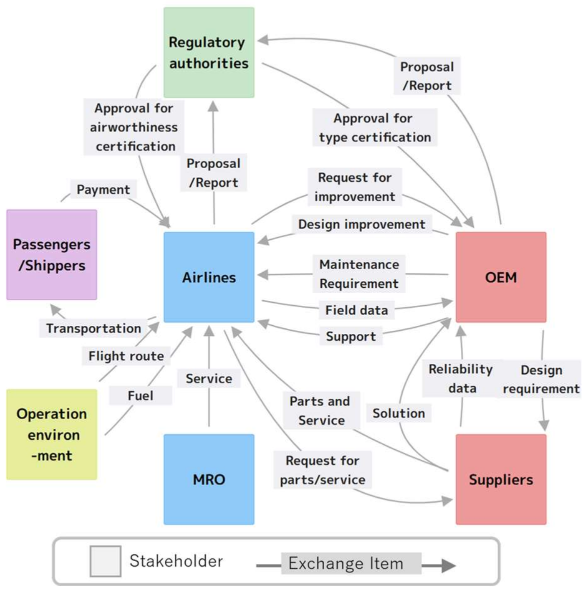

Figure 3. View (2) Stakeholder Context

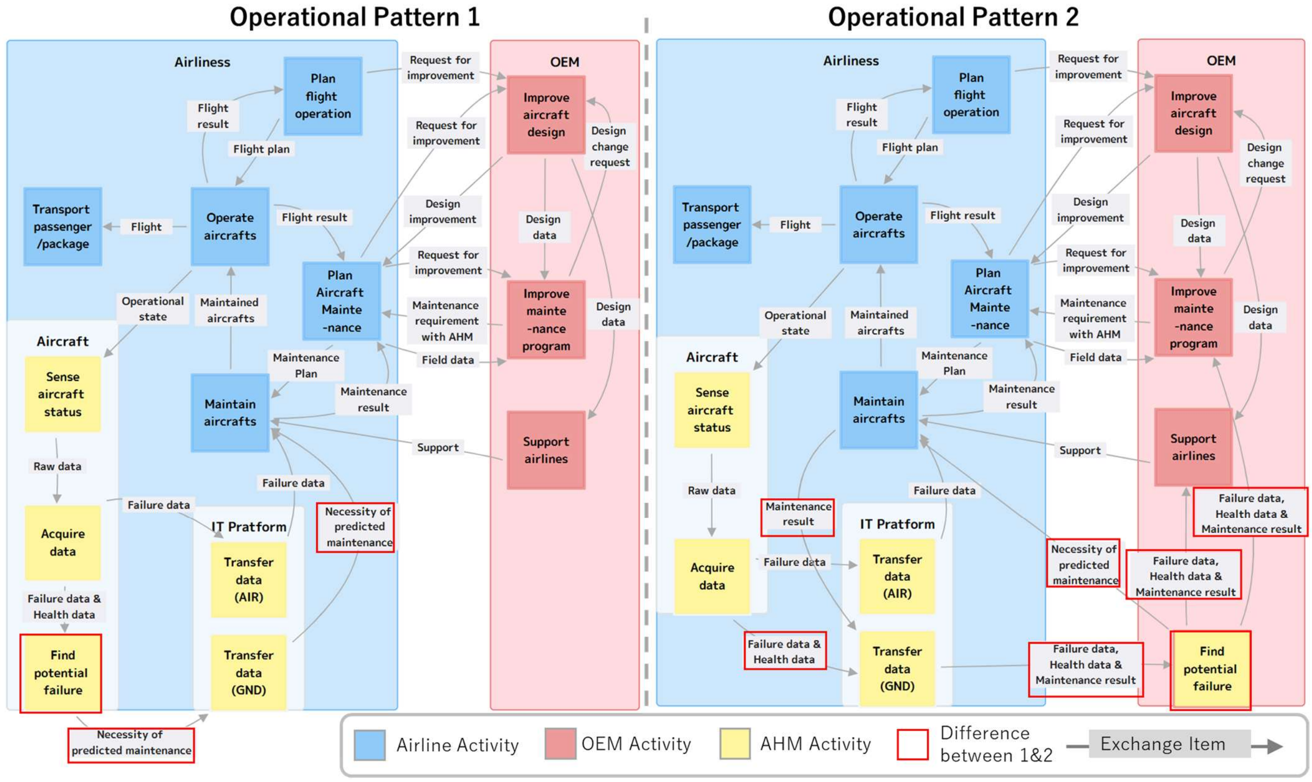

Figure 4. View (3) Operational Process

enhance profits, in addition to increasing after-service sales revenue. Airlines aim to maintain operational safety and quality, increase flight operations, and enhance profits. In addition to those, they address mechanic workforce reduction. The increase in aviation demand is shown to be a common driver for the OEM's goal of increasing aircraft production numbers and airlines' goal of increasing flight operations. Additionally, the decrease in mechanic candidates is shown to be a common driver for the OEM's after-service sales revenue increase and airlines' required mechanic reduction. The capabilities that can influence these drivers are described. Furthermore, the ultimate outcomes obtained through the effects brought about by capabilities are shown. Those are increased number of operating aircraft, improved operational reliability, reduced required mechanics, and increased aviation transportation volume. This explicitly describes how the drivers related to goals act as inputs to the SoS architecture and the outcomes act as outputs.

2.3. Operational Process View

Figure 3 shows the static context of stakeholders in civil aircraft aviation operation and maintenance using View (2). It describes relationships between stakeholders: passengers/shippers, airlines, OEMs, MROs, suppliers, and regulatory authorities.

Figure 4 shows the dynamic context between airlines and OEMs using View (3). It describes how AHM is implemented within the context of civil aviation operation and maintenance consisting of passengers/shippers, airlines, OEMs, MROs, suppliers, and regulatory authorities.

In operation/maintenance activities, airlines provide transportation services to passengers and shippers through aircraft operations, while OEMs provide aircraft after-services as well as design improvements and maintenance program enhancements to maintain/improve operational quality (Koizumi, 2023). Parts delivery results from suppliers are utilized by OEMs as component reliability information. Regulatory authorities approve applications related to airline airworthiness and OEM type certification.

Two operational process patterns are described for AHM implementation in aircraft operations activities.

Operational Pattern 1 shows the process where prognostic detection before failure occurrence by AHM is completed within the aircraft, and detection results are transmitted from the aircraft to the ground.

Operational Pattern 2 shows the process where prognostic detection before failure occurrence by AHM is conducted on the ground using information transmitted from the aircraft to the ground. In this case, OEMs collect and transmit aircraft

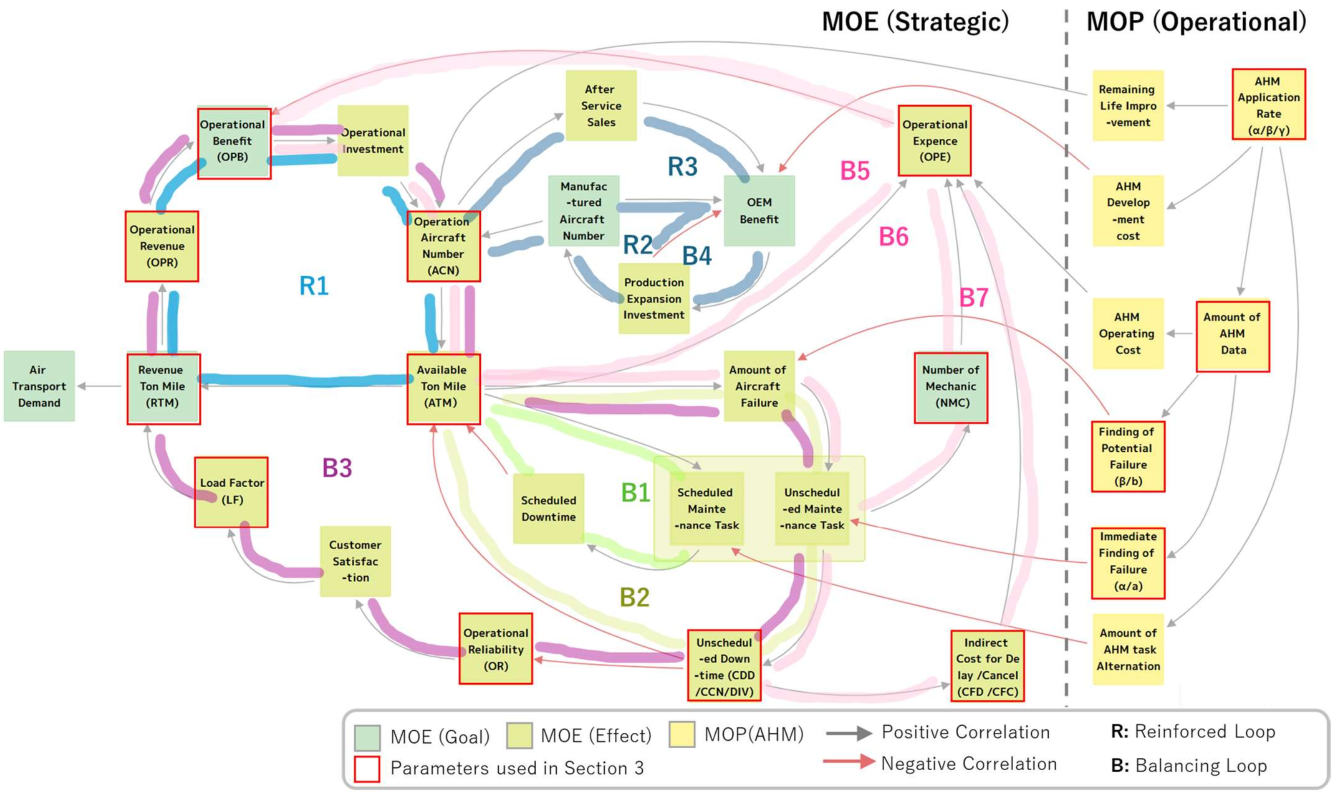

Figure 5. View (4) Parametric Causal Loop

health data, maintenance-related data, aircraft conditions, and maintenance work results as AHM data, and notify proactive maintenance based on prognostic detection before failure occurrence (JADC, 2024) (IADF, 2014). The AHM data collected is also used for medium- to long-term improvements of maintenance programs (IADF, 2014). Data transmission routes include two pathways: air-to-ground and ground routes, where data used for immediate failure notification utilizes the air-to-ground route, and data related to prognostic detection before failure occurrence utilizes the ground route. The transmission of AHM data utilizes IT platforms provided by specialized companies (Collins Aerospace, 2021).

AHM functions are distributed across OEMs, airlines, and IT platform providers, and multiple operational patterns beyond the two presented patterns are conceivable.

2.4. Causal Loop View

The relationship between the effects and outcomes desired by the capabilities constituting civil aviation and the goals of society, OEMs, and airlines, as well as the relationship between MoE and MoP, which are the operational effects obtained through AHM implementation, are shown using View (4). Table 2 shows the relationship between goals, outcomes, effects, and MoE. Figure 5 hows the causal loops between MoEs on the left side, and shows the relationship between AHM activities and MoP on the right side. The causal loops are composed of reinforcing loops where parameter structures strengthen each other and balancing loops that converge. As shown in Figure 5 left, this causal loop consists of three reinforcing loops (R1-R3) and seven balancing loops (B1-B7) described below.

R1: As revenue transportation increases, operational revenue and benefit increase, leading to increased operational investment. This increases the number of operational aircraft and transportation supply capacity, resulting in a reinforcing loop that increases revenue transportation.

R2: As the number of manufactured aircraft increases, OEM benefit increases, forming a reinforcing loop that expands manufacturing capacity.

R3: The increase in the number of operational aircraft increases after-service sales, which increases OEM benefit and, like R2, forms a reinforcing loop that increases the number of manufactured aircraft.

B1: As transportation supply capacity increases, downtime due to scheduled maintenance increases, forming a balancing loop that reduces transportation supply capacity.

B2: As transportation supply capacity increases, unplanned downtime (delays and cancellations) due to unscheduled maintenance caused by aircraft failures increases, forming a balancing loop that reduces transportation supply capacity.

B3: As transportation supply capacity increases, unplanned downtime (delays and cancellations) and unscheduled maintenance due to aircraft failures increases, reducing operational reliability and forming a balancing loop where customer satisfaction decreases, leading to reduced load factors.

B4: Increased manufacturing capacity leads to increased fixed costs, which pressures OEM profit. This becomes a balancing loop that inhibits the R2 reinforcing loop.

B5: As transportation supply capacity increases, operational costs increase. This becomes a balancing loop that inhibits the R1 reinforcing loop.

B6: The increase in transportation supply capacity leads to an increase in the number of required scheduled and unscheduled maintenance tasks, the number of mechanics, and increased operational costs. This becomes a balancing loop that inhibits the R1 reinforcing loop.

B7: As unplanned downtime increases, indirect costs associated with delays and cancellations increase, leading to increased operational costs. This becomes a balancing loop that inhibits the R1 reinforcing loop.

Next, Figure 5 right shows the effect of MoP from AHM activities on the causal loops composed of MoE. By increasing the AHM adoption rate, the effects of remaining useful life, failure detection rate, failure prediction rate, and replacing conventional maintenance with AHM are promoted. The improvement of remaining useful life through AHM implementation strengthens R1, increased failure detection rate improves B2, B6, and B7, increased failure prediction rate improves B6 and B7, and increased replacement of existing maintenance with AHM improves B1, B6, and B7. On the other hand, increased AHM adoption rate increases AHM operational costs due to increased AHM data volume, which adversely affects B5, B6, and B7. Furthermore, increased AHM development costs affect R2, which can be analytically understood to lead to decreased aircraft manufacturing.

Through these analyses, it was clarified that the causal relationships of AHM implementation on transportation supply capacity, operational reliability, and the number of mechanics can be qualitatively understood. The next section presents an example of optimizing AHM implementation effects. Note that only the parameters highlighted with red frame in Figure 5 are considered in the next section's analysis.

3. OPTIMIZATION OF AHM ADOPTION

In this section, AHM implementation in civil aircraft maintenance is evaluated and optimized based on the SoS architecture described in the previous section.

Table 2. MoE of Strategic Elements.

Type	Strategic Element	MoE	Symbol
Social Goal	Satisfy transportation demand	Air Transport Demand	-
Airline Goal	Increase airlines benefit	Operational Benefit	OPB
	Increase number of flights	Revenue Ton Mile	RTM
	Reduce number of mechanics	Improvement Number of Mechanic	I_{RMC}
OEM Goal	Increase OEM benefit	OEM Benefit	-
	Increase number of aircraft	Manufactured Aircraft Number	M_{ACN}
	Increase after service	After Service Sales	-
Out -come	Increased Air Transportation	Available Ton Mile	ATM
	Increased Number of Operational Aircraft	Operation Aircraft Number	ACN
	Higher Operational Reliability	Operational Reliability	OR
	Required Number of Mechanic	Number of Mechanic	NMC
Effect	Increased Production Expansion Investment	Production Expansion Investment	-
	Increased Operational Investment	Operational Investment	-
	Increased Manufactured Aircraft	Manufactured Aircraft Number	M_{ACN}
	Higher Aircraft Reliability	Amount of Aircraft Failure	-
	Less Scheduled Maintenance	Scheduled Maintenance Task	-
	Less Unscheduled Maintenance	Unscheduled Maintenance Task	-
	Higher Aircraft Availability	Unscheduled Downtime	CDD, CCN, DIV
		Scheduled Downtime	-
	Higher Labor Efficiency of Mechanic	Labor Productivity	LP

In this study, Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb, Pratap, Agarwal, Meyarivan, 2002) was adopted and implemented according to the characteristics of the AHM problem. Using the AHM application rates for AHM functions that predict failures and notify maintenance necessities before failure occurrence and AHM functions that notify during failure occurrence (before landing) as variables, optimization is performed with operational reliability, airline benefit, mechanic reduction rate, and AHM data volume as objective functions. The optimization is conducted for the two operational patterns shown in Figure 4. This enables comparative evaluation of the effects brought by AHM under two operational patterns when aviation transportation demand doubles.

3.1. Formulations

The relationships between MoE and MoP shown in Figure 5 are formulated as equations (1) to (11). Table 3 shows the MoE as indicators for measuring AHM implementation effects, and Table 4 shows the MoP required in the process of deriving these indicators. Operational reliability is selected as an indicator for measuring AHM implementation effects. Conventionally, TDR (Dispatch Reliability) has often been used as an indicator for evaluating reliability, but TDR does not reflect the maintenance required for aircraft recovery due to technical defects, and operational reliability is more suitable for determining fleet utilization rate trends (IATA, 2022a).

The selection of MoP was premised on using data from U.S. DOT Form 41, which the U.S. Department of Transportation requires U.S. airlines to report and publishes on its website. This database is utilized in the Global Airline Industry Program aimed at building a knowledge system to understand the development, growth, and competitive advantages of the large-scale and complex commercial aviation industry by MIT. Additionally, Ueda & Hidaka (2024) have reported analysis results of commercial aircraft maintenance cost structure using this database. Some numerical values that could not be obtained from publicly available information were set as assumed values.

Equation (1) shows the relationship between operational reliability and delay, cancellation, and diversion rates. Equation (2) shows the improvement rate of operational reliability resulting from improvements in delays and cancellations due to AHM implementation. Equation (3) shows the improvement amount of delay time as the product of the total of airline-caused delay time and subsequent flight delay time and the AHM application rate. Equation (4) shows the improvement amount of cancellation time as the product of airline-caused cancellation time and the AHM application rate. Equation (5) calculates the profit obtained from AHM implementation as the sum of increased operational profit and the cost reduction effect of indirect costs due to delays and cancellations. Equation (6) shows the number of mechanics reduced due to AHM implementation, calculated from the mechanic constraint time during improved delay and cancellation occurrences and the annual working hours per mechanic. Equation (7) shows the total cost that can be spent on AHM as the product of the ratio between the total profit obtained by multiplying the profit from AHM implementation by the average aircraft lifetime and the number of manufactured aircraft of the AHM development target model. Equations (8) and (9) are used to calculate parameters included in equations (1) and (2), respectively. Equation (10) shows the air-to-ground data transmission volume, and equations (11)-1 and (11)-2 show the ground-to-ground data transmission volumes for operational patterns 1 and 2, respectively. Equation (10) is common to both patterns.

$$\mathrm{OR} = 1 - \frac{1}{\mathrm{FLT}}(\mathrm{CDD} + \mathrm{CCN} + \mathrm{DIV}) + \mathrm{I_{OR}} - \mathrm{I_{OR_p}} \tag{1}$$

$$\mathrm{I}_{OR} = \left(\frac{\mathrm{IAH_D}}{\mathrm{DF_D}} + \frac{\mathrm{IAH_C}}{\mathrm{DF_C}}\right) \times \frac{1}{\mathrm{FLT}} \tag{2}$$

$$\mathrm{IAH_D} = \left(\mathrm{CDDH} + \frac{\mathrm{LAD} \times \mathrm{CDDH}}{\mathrm{DDH} - \mathrm{LAD}}\right) \times \frac{\gamma(a\alpha_D + b\beta_D)}{1 - \gamma(a\alpha_D + b\beta_D)} \tag{3}$$

$$\mathrm{IAH_C} = \left(\mathrm{CCN} \times \mathrm{DFC}\frac{\gamma(a\alpha_\mathrm{C} + b\beta_\mathrm{C})}{1 - \gamma(a\alpha_\mathrm{C} + b\beta_\mathrm{C})}\right) \tag{4}$$

$$\mathrm{AHM_B} = (\mathrm{OP_R} - \mathrm{OP_E})\frac{\mathrm{IAH_D} + \mathrm{IAH_C}}{\mathrm{AH}} + \left(\mathrm{IAH_D} \times \mathrm{CF_D} + \frac{\mathrm{IAH_C}}{\mathrm{DF_C}}\mathrm{CF_C}\right) \tag{5}$$

$$\mathrm{I_{RMC}} = \left\{\frac{\mathrm{CDDH}\ \gamma(a\alpha_D + b\beta_D)}{1 - \gamma(a\alpha_D + b\beta_D)} + \mathrm{IAH_C}\right\} \times \frac{1}{\mathrm{NMC} \times \mathrm{YWH} \times \mathrm{LP}} \tag{6}$$

$$\mathrm{AHM_C} = \mathrm{AHM_B}\ \frac{\mathrm{M_{ACN}}}{\mathrm{ACN}}\ \mathrm{AAL} \tag{7}$$

$$\mathrm{CCD} = \frac{\mathrm{CDDH} \times \mathrm{DD}}{\mathrm{DDH}} \tag{8}$$

$$\mathrm{DF_D} = \frac{\mathrm{DDH}}{\mathrm{DD}} \tag{9}$$

$$\mathrm{AOD_{AIR}} = \mathrm{NOF} \times (\alpha_C + \alpha_D) \times \mathrm{AFR} \times \mathrm{AH} \tag{10}$$

$$\mathrm{AOD_{GND\_1}} = \mathrm{NOF} \times (\beta_C + \beta_D) \times \mathrm{AFR} \times \mathrm{AH} \tag{11-1}$$

$$\mathrm{AOD_{GND\_2}} = \mathrm{NOF} \times (\beta_C + \beta_D) \times \mathrm{AH} \times \mathrm{SR} \tag{11-2}$$

Table 3. MoE of AHM implementation

MoE	Symbol
Improvement of OR	I_{OR}
Improvement of OR (Present)	I_{OR_P}
Improvement of Air Hour by Cancel	IAH_C
Improvement of Air Hour by Delay	IAH_D
AHM Benefit ($B)	AHM_B
AHM Cost Limitation	AHM_C
Improvement Number of Maintenance Crew	I_{NMC}
Improvement Rate of Maintenance Crew	I_{RMC}

Table 4. MoP of AHM implementation

MoP	Symbol
Average Aircraft Life	AAL
Air Hour	AH
Aircraft Failure Rate	AFR
Amount of Data (AIR)	AOD_{AIR}
Amount of Data (GND) of Pattern 1	AOD_{GND_1}
Amount of Data (GND) of Pattern 2	AOD_{GND_2}
Carrier Cancellation Number	CCN
Carrier Departure Delay Number >15min	CDD
Carrier Delay Hour	CDDH
Departure Delay Number >15min	DD
Departure Delay Hour	DDH
Downtime Hour For Cancel	DFC
Downtime Hour For Delay	DFD
Diverted Number	DIV
Number of Flight	FLT
Late Aircraft Delay Hour	LAD
Number of Functions	NOF
Sampling Rate	SR
Yearly Work Hour per crew	YWH
Airlines AHM Adoption Rate	γ
Rate of AHM on-time indication for failure cause cancel	α_C
Rate of AHM on-time indication for failure cause delay	α_D
Rate of AHM failure prediction for failure cause cancel	β_C
Rate of AHM failure prediction for failure cause delay	β_D
Rate of downtime improvement by AHM on-time failure indication	a
Rate of downtime improvement by AHM predicted failure indication	b

Table 5. Data of Delta Airlines of 2023

Symbol	2023	2045	Source
RTM	2.34E+10	4.68E+10	FORM 41, Air Carrier Summary: T2: U.S. Air Carrier TRAFFIC And Capacity Statistics by Aircraft Type (U.S. DOT, 2024)
ATM	3.83E+10	7.66E+10*	
FLT	9.85E+05	1.97E+06*	FORM41, On-Time: Reporting Carrier On-Time Performance (1987-present) (U.S. DOT, 2024)
AH	2.05E+06	4.11E+06*	
DDH	2.15E+05	4.30E+05*	
CDDH	9.41E+04	1.88E+05*	
LAD	5.45E+04	1.09E+05*	
DD	1.67E+05	3.35E+05*	
CCN	2.17E+03	4.34E+03*	
DIV	2.04E+03	4.08E+03*	
ACN	969	19438*	FORM41, Air Carrier Financial: Schedule B-43 Inventory (U.S. DOT, 2024)
OPR	58.2	116.4*	FORM41, Air Carrier Financial: Schedule P-1.2 (U.S. DOT, 2024)
OPE	51.9	103.8*	
CFD	10	10	IATA (2023) (2022b)
CFC	100	100	
NMC	9267	18534*	FORM41, Air Carrier Financial: Schedule P-10 (U.S. DOT, 2024)
LP	0.65	0.65	Clark. (2017)
DFC	6	6	Assumptions
YWH	1600	1600	
a	0.2	0.2	
b	0.4	0.4	
M_{ACN}	3000	3000	
AAL	20	20	
NOF	3000	3000	
AFR	1.0E-05	1.0E-05	
SR	60	60	

* The 2024 values are estimated values for Pattern 1 based on the 2023 values. Assumed to increase proportionally to RTM.

3.2. Parameters

For calculating AHM implementation effects, the 2023 Delta Air Lines data shown in Table 5 and the predicted values for

2045 based on it are used. It is known that Delta Air Lines has already implemented AHM since 2017 (Boeing, 2017). Therefore, assuming that AHM is already applied. Load factors, fleet composition ratio, and unit time cost of mechanics are assumed to be constant. The improvement in operational reliability of present (I_{OR_P}) due to the partial application of AHM's immediate failure notification function already implemented, is 1.9%.

3.3. Optimization

In this study, five decision variables (γ: Airlines AHM Adoption Rate, α_C/α_D: immediate notification rate, β_C/β_D: pre-failure notification rate) and four objective functions (OR: operational reliability, AHM_B,: AHM benefit, I_{RMC}: mechanic reduction rate, AOD_{GND}: amount of ground transferred data) were set.

As constraint conditions, following variable range are set.

$$0 \leq \alpha_C + \beta_C \leq 1 \quad (12)$$

$$0 \leq \alpha_D + \beta_D \leq 1 \quad (13)$$

$$0 \leq \gamma < 1 \quad (14)$$

$$0 < 1 - \gamma\left(a\,\alpha_C + b\,\beta_C\right) \quad (15)$$

$$0 < 1 - \gamma\left(a\,\alpha_D + b\,\beta_D\right) \quad (16)$$

To treat all four objective functions uniformly as maximization problems, the sign of AOD_{GND} was inverted. In dominance determination, a dominant relationship was recognized when one vector had superiority or inferiority to another vector in all objectives and was strictly superior to at least one objective.

Blend Crossover-α (BLX-α) crossover was adopted for crossover operations, achieving effective search that leverages the continuity of real variables. For mutation, a two-stage method was implemented where each gene is independently mutated, and constraint correction is performed after mutation. Tournament selection was used for selection operations, applying selection criteria with rank priority and crowding distance as secondary priority.

In the experiments, population size was set to 50, maximum generations to 100, crossover rate to 0.9, mutation rate to 0.1, and tournament size to 2. These values were determined considering the balance between computational efficiency and solution quality. In particular, the population size considered the trade-off between appropriate diversity maintenance and computational cost in the 5-variable 4-objective problem.

To investigate the impact of different calculation methods for ground data transmission volume on optimization results, experiments were conducted with two operational patterns. Operational Pattern 1 adopted equation (11-1), and Operational Pattern 2 adopted equation (11-2), with optimization executed independently for each.

To select practical compromise solutions from the obtained Pareto optimal solution set, a normalized total score method was implemented. After normalizing each objective function value to the [0,1] interval, the solution with the maximum total score was selected as the compromise solution.

Table 6 shows the optimization calculation results. Regarding decision variables, regardless of pattern, the AHM adoption rate by airlines tends to be high. Furthermore, regardless of pattern, for failures leading to cancellations, immediate notification was higher than preventive notification, while for failures leading to delays, the ratio of preventive notification tended to be high. Regarding objective functions, regardless of pattern, operational reliability and AHM benefit showed high improvement rates, but the mechanic reduction rate did not improve significantly.

The largest difference when comparing patterns was the ground-to-ground data transmission volume, with a 6 million fold difference. This difference is due to Pattern 1 continuously transmitting health information at a constant rate, while Pattern 2 transmits only when failures are predicted onboard the aircraft.

Overall, it was found that by raising the application rate of AHM functions that predict failure β_D) to approximately 85%, benefits on the scale of $1.5B can be achieved. In this case, Pattern 1 can be considered realistic from the perspective of data transmission volume.

Table 6. Optimized Result.

Type	Parameter	Current	Pattern 1	Pattern 2
Decision Valliables	γ	0.8	0.98	0.97
	α_C	1.0	0.75	0.79
	α_D	0.67	0.17	0.097
	β_C	0.0	0.10	0.031
	β_D	0.0	0.83	0.89
Objective Value	OR	95.3%	95.8%	95.9%
	AHM_B	$0.49B	$1.96B	$1.99B
	I_{RMC}	0.55%	0.58%	0.59%
	AOD_{GND}	0	1.2E+05	6.8E+11

4. CONCLUSION

In a business environment where passenger demand is expected to increase in the future, optimal solutions were examined for how OEMs should allocate their limited resources to maximize the value (profit, operational reliability, mechanic efficiency) that airlines can obtain by implementing AHM.

The implementation of AHM in civil aircraft maintenance was described as two patterns of SoS architecture using UAF. The relationships between parameters of elements constituting the SoS architecture were captured as causal loops and formulated. This enabled quantitative evaluation of the effects of AHM and impacts on stakeholder goals by changing AHM operational patterns and AHM application rates, and multi-objective optimization of AHM application rates for each AHM operational pattern.

As a result of optimization, it was found that for optimizing AHM implementation rates in both operational patterns, it is important to raise the application rate of AHM functions that predict failure (β_D) to approximately 85%, which can bring benefits on the scale of $1.5B. On the other hand, it was found that the improvement effect on mechanic reduction rates is limited. Furthermore, from the perspective of data transmission volume, Pattern 1, which predict failure onboard the aircraft, can be considered realistic under current conditions. However, it should be noted that adding failure prediction functions to aircraft presents the problem of enormous development costs compared to ground-based responses.

This study targeted simple differences in operational architecture, but it can be applied to more detailed architectural differences. Additionally, while this study optimized four objectives using five parameters related to AHM implementation rates, it can be used for more specific requirement considerations necessary for designing AHM systems in accordance with the issues shown in Future Work.

FUTURE WORK

Future challenges are shown below.
Matters related to airlines:

- The current results do not show much effect on mechanic reduction. There is a possibility that the relationship between the reduction of conventional maintenance work due to AHM implementation and the number of mechanics employed is not captured, and additional investigations such as interviews with airlines are necessary.
- Since the mechanism of data transmission pricing was unclear, the objective function was changed from data cost to data volume.
- The variation in AHM implementation effects among different types of airlines is not considered.

Matters related to OEMs:

- The difference in AHM development costs between onboard and ground-based failure prediction is not considered.
- The relationship between OEM revenue increase due to AHM implementation is unclear and therefore not included in the evaluation.

Matters related to AHM technology:

- The relationship between the amount of data used for failure prediction and prediction accuracy is not considered.
- The effect of increased aircraft and component lifespan due to AHM implementation is not considered.
- The limitations of data download volume from aircraft on the ground are not considered.

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REFERENCES

Aoyama, T., Mizobuchi, Y., & Hashimoto, A. (2024). Research and development of aircraft lifecycle DX technology for creating new aircraft. Journal of the Japan Society for Aeronautical and Space Sciences, vol. 72(6), pp. 193-199. (in Japanese)

Boeing. (2017). Boeing Highlights Analytics Capability with Customer Orders, New Name. https://boeing.mediaroom.com/2017-06-19-Boeing-Highlights-Analytics-Capability-with-Customer-Orders-New-Name

Brunton, S. L., Nathan Kutz, J., Manohar, K., Aravkin, A. Y., Morgansen, K., Klemisch, J., Goebel, N., Buttrick, J., Poskin, J., Blom-Schieber, A. W., Hogan, T., & McDonald, M. (2021). Data-driven aerospace engineering: reframing the industry with machine learning. AIAA Journal, vol. 59(8), pp. 2820-2847.

Clark, P., (2017). Buying the Big Jets Fleet Planning for Airlines. Third Edition. Routledge

Collins Aerospace, (2021). Understanding the Impact of Aircraft Information Data From New Generation Aircraft on the ACARS Network, White Paper.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T. (2002), A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation, 6, 2, pp. 182-197.

Hölzel, N. B., & Gollnick, V. (2015). Cost-benefit analysis of prognostics and condition-based maintenance concepts for commercial aircraft considering prognostic errors. Annual Conference of the Prognostics and Health Management Society.

Hu, Y., Miao, X., Si, Y., Pan, E., & Zio, E. (2022). Prognostics and health management: A review from the perspectives of design, development and decision. Reliability Engineering & System Safety, vol. 217, pp. 108063.

Hussain, Y. M., Burrow, S., Henson, L., & Keogh, P. (2016). Benefits analysis of prognostics & health monitoring to aircraft maintenance using system dynamics. European Conference of the Prognostics and Health Management Society.

IATA. (2022a). Aircraft Operational Availability (2nd ed.). https://www.iata.org/contentassets/bf8ca67c8bcd4358b3d004b0d6d0916f/aoa-2nded-2022.pdf

IATA. (2022b). IATA Ground Damage Report the case for enhanced ground support equipment. https://www.iata.org/en/programs/ops-infra/ground-operations/ground-damage-report/

IATA. (2023). From Aircraft Health Monitoring to Aircraft Health Management White Paper on AHM – Position Update. https://www.iata.org/en/programs/ops-infra/techops/mctg/

International Aircraft Development Fund [IADF]. (2014). History and mechanism of AHM, and Boeing 787 AHM. Kaisetsu Gaiyo, vol. 26(6). (in Japanese)

International Standards Organization (ISO). (2011). ISO/IEC/IEEE 42010: Systems and software engineering – Architecture Description.

Ito, K. (2013). Optimal maintenance policy for civil aircraft. REAJ Journal, vol. 35(1), pp. 18-23. (in Japanese)

Japan Aircraft Development Corporation [JADC]. (2024). Market forecast for commercial aircraft 2025-2044. YGR-5145. (in Japanese)

Jensen, G., Dan, E. E., Kihlström, L.-O., Altamiranda, E., & Hause, M. (2024). Model-based maintenance planning and analytics for oil & gas offshore systems. 35th Annual INCOSE International Symposium.

Koizumi, T. (2023). Development method of maintenance program in commercial aircraft development. Journal of the Japan Society for Aeronautical and Space Sciences, vol. 71(4), pp. 91-98. (in Japanese)

Koizumi, T., & Kogiso, N. (2024a). An effectiveness evaluation method using system of systems architecture description of aircraft health management in aircraft maintenance program. International Journal of Prognostics and Health Management, vol. 15(3), pp. 3837.

Koizumi, T., & Kogiso, N. (2024b). Trade-off analysis from system of systems perspective for AHM adoption to civil aircraft maintenance. Proceedings of the 34th Design Engineering and Systems Conference of JSME, 1409. (in Japanese with English abstract)

Koizumi, T., Morino, H., Hara, T., & Aoyama, K. (2025). Stakeholder harmonization of hydrogen supply business: An UAF approach to system dynamics in enterprise architecture and product service systems. 35th Annual INCOSE International Symposium.

Kordestani, M., Orchard, M. E., Khorasani, K., & Saif, M. (2023). An overview of the state of the art in aircraft prognostic and health management strategies. IEEE Transactions on Instrumentation and Measurement, vol. 72, pp. 1-15.

Kunche, S., Chen, C., & Pecht, M. (2012). A review of PHM system's architectural frameworks. The 54th Meeting of the Society for Machinery Failure Prevention Technology.

Levii Inc. (2023). Balus. https://levii.co.jp/services/balus

Liu, F., & Huang, Z. (2015). System dynamics based simulation approach on corrective maintenance cost of aviation equipments. Procedia Engineering, vol. 99, pp. 150-155.

Martin, J. N. (2025). Enabling enterprise transformation using system principles and concepts. 35th Annual INCOSE International Symposium.

Meissner, R., Meyer, H., & Wicke, K. (2021). Concept and economic evaluation of prescriptive maintenance strategies for an automated condition monitoring system. International Journal of Prognostics and Health Management, vol. 12(3).

Ministry of Land, Infrastructure, Transport and Tourism. [MLIT] (2025). Final report of the study group on securing and utilizing aircraft maintenance engineers and pilots. https://www.mlit.go.jp/koku/koku_tk5_000146.html (in Japanese)

MIT. (n.d.). Global Airline Industry Program. https://web.mit.edu/airlines/

Miura, M., & Sakamoto, Y. (2023). Interactive system modeling for designing a new concept launch vehicle. Aerospace Europe Conference 2023 – 10th EUCASS - 9th CEAS.

Olsson, E., Funk, P., Candell, O., Sohlberg, R., & Karim, R. (2021). Enterprise modeling for dynamic matching of tactical needs and aircraft maintenance capabilities. 15th International Conference and Workshop on Industrial AI.

Rodrigues, L. R., Gomes, J. P. P., Ferri, F. A. S., Medeiros, I. P., Galvão, R. K. H., & Nascimento Júnior, C. L. (2015). Use of PHM information and system architecture for optimized aircraft maintenance planning. IEEE Systems Journal, vol. 9(4), pp. 1197-1207.

Sriram, C., & Haghani, A. (2003). An optimization model for aircraft maintenance scheduling and re-assignment. Transportation Research Part A: Policy and Practice, vol. 37(1), pp. 29-48.

Sterman, J. D. (2000). Business dynamics: Systems thinking and modeling for a complex world. Boston, MA: Irwin/McGraw-Hill.

Teubert, C., Pohya, A. A., & Gorospe, G. (2023). Analysis of barriers preventing the widespread adoption of predictive and prescriptive maintenance in aviation. NASA TM–20230000841.

The Object Management Group [OMG]. (2022). Enterprise architecture guide for UAF (Informative). Formal/22-07-10. https://www.omg.org/spec/UAF/1.2

Ueda, Y., & Hidaka, K. (2024). A study of homogeneity and heterogeneity in maintenance costs for commercial aircraft. Transactions of the Japan Society for Aeronautical and Space Sciences, vol. 72(2), pp. 41-47. (in Japanese with English abstract)

U.S. Department of Transportation. (2024). Bureau of Transportation Statistics. https://www.transtats.bts.gov/homepage.asp

Verhoeff, M., Verhagen, W. J. C., & Curran, R. (2015). Maximizing operational readiness in military aviation by optimizing flight and maintenance planning. Transportation Research Procedia, vol. 10, pp. 941-950.

Vianna, W. O. L., & Yoneyama, T. (2018). Predictive maintenance optimization for aircraft redundant systems subjected to multiple wear profiles. Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management, pp. 1654-1658.

Wang, L., Chen, Y., Zhao, X., & Xiang, J. (2024). Predictive maintenance scheduling for aircraft engines based on remaining useful life prediction. IEEE Internet of Things Journal, vol. 11(13), pp. 22156-22168.