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A digital twin-enhanced collaborative maintenance paradigm for aero-engine fleet

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Abstract Maintenance of aero-engine fleets is crucial for the efficiency, safety, and reliability of the aviation industry. With the increasing demand for air transportation, maintaining high-performing aero-engines has become significant. Collaborative maintenance, specifically targeting aero-engine fleets, involves the coordination of multiple tasks and resources to enhance management efficiency and reduce costs. Digital Twin (DT) technology provides essential technical support for the intelligent operation and maintenance of aero-engine fleets. DT maps physical object properties to the virtual world, creating high-fidelity, dynamic models. However, DT-enhanced collaborative maintenance faces various challenges, including the construction of complex system-layer DT models, management of massive integrated DT data, and the development of fusion mechanisms and decision-making methods for DT data and models. Overcoming these challenges will allow the aviation industry to optimize aero-engine fleet maintenance, ensuring safety, efficiency, and cost-effectiveness while meeting the growing demand for air transportation.

Keywords aero-engine fleet, collaborative maintenance, Digital Twin (DT), complex system

1 Introduction

The aviation industry consistently leads in technological innovation, continuously seeking ways to improve the efficiency, safety, and reliability of air travel (Tahan et al., 2017). Central to these efforts are the rigorous monitoring and maintenance of aero-engines, which serve as the foundation of modern aircraft (Liu, 2020). Ensuring optimal performance of aero-engines is not only critical for commercial airlines but also for the safety and satisfaction of the countless passengers who rely on air travel daily. As the demand for air transportation increases, the importance of maintaining high-performing aero-engines continues to grow (Rath et al., 2022).

Aero-engines, being the vital component of aircraft, require maximum reliability and safety (Sun et al., 2015). However, these engines consist of highly complex aerothermal rotating machinery with numerous components. Many of these components operate under extreme conditions, such as high temperature, pressure, rotational speed, vibration, and ever-changing environments. They often endure significant loads and thermal shocks (Sun et al., 2016). As a result, they are prone to failures and exhibit characteristics such as multiple failure modes and composite failures (Qi et al., 2022). Moreover, in recent years, aero-engines have witnessed increasing performance requirements, including higher thrust-to-weight ratios, increased compressor pressure ratios, and elevated turbine inlet temperatures (Zhu et al., 2017). This intensifies the severity of operating conditions for critical components and imposes stringent performance demands, highlighting the growing importance of reliability and safety concerns for aero-engines (Zhao and Chen, 2022).

The importance and significant value of the aero-engine maintenance industry have driven continuous research and advancements in the field. Since the 1960s,

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countries, led by the United States, have been developing aero-engine maintenance technologies through stages including condition monitoring, performance evaluation, and fault diagnosis. The emergence of Engine Health Monitoring systems in the 1970s (Sun et al., 2013), Full Authority Digital Engine Controls (FADEC) in the 1980s (Chen et al., 2009), and the successful application of Prognosis and Health Management technology in the late 1990s have significantly improved engine troubleshooting (Zhang et al., 2022).

However, traditional research on aero-engine maintenance typically focuses on individual engines. With the rise of the collaborative manufacturing concept (Wang et al., 2016), a maintenance approach targeting aero-engine fleets has been proposed. Aero-engine fleets, which typically refer to all engines under an airline or an airbase, serve as the fundamental units for realizing collaborative maintenance (Safaei et al., 2011; Gavranis and Kozanidis, 2017). Collaborative maintenance targeting aero-engine fleets involves coordinating multiple maintenance tasks and utilizing various maintenance resources. Employing collaborative maintenance methods can enhance management efficiency and reduce maintenance costs, to some extent resolving the contradiction between safety and cost-effectiveness (Jenab and Zolfaghari, 2008). Addressing the collaborative maintenance of the aero-engine fleet requires addressing three key questions: *What is the current operating state of the aero-engine fleet? How to develop an aero-engine fleet maintenance plan? and How should the aero-engine fleet be specifically maintained?* In order to tackle these questions, a technology system is needed that can analyze equipment mechanisms and enable complex system collaboration.

Digital Twin (DT) is widely recognized as a key solution for the digitalization and upgrading of manufacturing processes and information technology (Tao et al., 2018; 2023; Wang et al., 2021). It enables the mapping of physical object properties, structure, state, performance, function, and behavior to the virtual world. This is achieved by establishing bidirectional mapping, dynamic interaction, and real-time connections between the physical and virtual domains. As a result, a high-fidelity, dynamic, multi-dimensional, multi-scale, and multi-physical quantity model is formed (Tao and Zhang, 2017; Tao et al., 2019; Tao and Qi, 2019). The application of DT technology has gained significant attention due to its potential in enhancing the health maintenance and security of aerospace vehicles. NASA's successful implementation of DTs in aircraft and rocket health management demonstrates the promising future of this technology in aircraft operations (Grieves and Vickers, 2017). Consequently, DT technology can provide crucial technical support for the intelligent operation and maintenance of an aero-engine fleet, enabling complex system-layer cyber-physical integration (Glaessgen and Stargel, 2012).

However, the implementation of DT-enhanced aero-engine fleet collaborative maintenance comes with its own set of challenges. Firstly, a complex system-layer DT model specifically designed for the aero-engine fleet is required to accurately describe and map the entire maintenance process. Secondly, managing the large amounts of data generated by the virtual-physical integration enabled by DT technology poses a challenge in terms of data fusion. Finally, there is a need for mechanisms to effectively integrate twin data and models, as well as analysis and decision-making methods.

2 How to construct multi-layer DT models

To address these challenges, constructing multi-layer DT models is crucial. The DT model is a digital representation of real-world entities or systems, capturing attributes, methods, behaviors, and other characteristics of physical entities and processes in the digital space. It can be used to represent, predict, optimize, and control the physical entity or system. In the field of equipment group management, the DT model can be divided into two levels: equipment level and system level. The equipment level DT model focuses on the performance and health state of individual equipment, incorporating the fusion of material physical properties model and performance model. The system-level DT model, on the other hand, focuses on the capability, efficiency, and robustness of the system, based on the equipment-level DT model and all relevant elements and processes (Qian et al., 2022; Tao et al., 2022).

Aero-engines comprise complex and intricate systems, consisting of numerous parts. From a spatial scale perspective, the DT model of an aero-engine can be divided into multiple layers based on granularity. These layers include the unit layer, system layer, and complex system layer. The unit layer refers to the smallest unit of the aero-engine, such as the fan blade, combustion chamber, turbine blade, exhaust nozzle, bearings, and seals. The system layer refers to aero-engine subsystems with different functions, including the air intake system, compression system, combustion system, turbine system, fuel system, lubrication system, engine control system, and so on. The complex system layer contains all subsystems that pertain to complete aero-engines with varying types, conditions, and health statuses. These three layers form an aero-engine DT model with multi-layer assembly and multi-dimensional fusion.

In comparison to the individual aero-engine DT model, the aero-engine fleet maintenance system belongs to the system-level DT model. In the system-level DT model, all relevant elements are aggregated, including not only the DT model of aero-engines but also the DT model of the external environment, maintenance resources, and

personnel. Conceptualize the system as a two-layer network model: the task layer and the service layer. The nodes of the task layer represent all the aero-engines, with their performance and health state extracted from the aero-engine DT model. Based on the aero-engine's performance and health state, multiple maintenance tasks are generated. In the service layer, all maintenance-related resources and personnel are considered as maintenance service nodes. The capability and state of the maintenance resources and personnel are derived from their DT model. Once the aero-engine fleet maintenance tasks are released, these services will be matched to the tasks to efficiently and accurately resolve any faults. To construct a complex system DT model that fulfills the aforementioned requirements, several key technologies must be addressed.

(1) Firstly, the aero-engine equipment level DT model requires multi-layer fusion technology. This entails integrating the geometry model, physics model, and performance models to accurately depict the spatial position relationship of aero-engine components and the coupling mechanism of their physical properties. This fusion ensures the correct assembly of the aero-engine equipment level DT model and enables the extraction of precise performance and health status parameters.

(2) Secondly, the aero-engine equipment level DT model migration technology is crucial. Constructing individual DT models for each aero-engine within a complex equipment group is a time-consuming and labor-intensive task. However, given that aero-engines of the same type share similarities in material, structure, and performance, it is possible to copy these similarities while preserving the differences, such as working environment, operating hours, and maintenance history. This approach significantly improves the efficiency of constructing the system-level DT model.

(3) Furthermore, the consistency of the aero-engine fleet DT model needs to be verified. Similar to physical entities, virtual models in the virtual space evolve based on a predefined mechanism and conditions of model evolution. However, small errors and time delays in interaction can accumulate and result in significant deviations between the model and the actual entity. The use of DT model consistency verification technology helps eliminate errors and maintains the desired consistency between the physical and virtual spaces.

(4) Moreover, for managers and researchers involved in aero-engine fleet maintenance, clear visual displays are essential for aid in research and decision-making. Visualizing the DT models is also crucial during the construction phase. Typically, equipment-level DT models are visualized using various 3D modeling tools, providing a visualization of their physical and performance parameters. System-level DT models, on the other hand, are visualized by plotting the network model and presenting statistical data.

3 How to manage multi-dimensional DT data

With the steady advancement of human science and technology, the scale of data that individuals possess and manage has been continuously expanding, from simple record-keeping to sophisticated database systems. DT data not only raw numerical and factual information about physical entities but also virtual model-related data, application-related data, and domain knowledge. The emergence of data in new dimensions presents fresh challenges in data management. In the domain of aero-engine fleet maintenance, DT data can be classified into two categories: equipment state data and fleet maintenance decision-making data (Wang et al., 2021; Zhang et al., 2021).

Equipment state physical data, falling under the aforementioned categories, includes aero-engine physical parameters and data acquired from various airborne sensors and external detection instruments. Virtual model data primarily pertains to performance data obtained through simulation and calculation of the aero-engine's DT model, conducted under different initial conditions. These virtual models, alongside equipment state data, serve as foundations for the development of applications such as condition monitoring, fault diagnosis, and fault prognosis. These applications comprehensively assess real-time conditions, failure categories, and remaining useful life of aero-engines. Domain knowledge, an integral part of DT data, guides aero-engine maintenance applications, such as performance monitoring thresholds and the aero-engine health status factor. Additionally, new domain knowledge can be acquired through analysis and mining of DT data, enabling constant updates and iterations.

Different from equipment state data, fleet maintenance decision-making data focuses on the overall state of the maintenance system. This data can be divided into four categories. The physical data comprises the state of the aircraft engine fleet, environmental conditions, maintenance resources, and personnel status. The virtual model-related data refers to the data derived from the DT model at the system level, specifically for aero-engine fleet maintenance. Based on fleet maintenance decision-making data and the system-level DT model, additional applications are developed, including fleet maintenance scheduling, flight plan creation, backup engine planning, and so forth. All historical and empirical data are synthesized and mined to form domain knowledge. With constant updates and iterations, domain knowledge enhances efficiency and robustness.

However, in order to achieve efficient management and iterative mining of DT data, numerous key technologies must be overcome.

(1) Aero-Engine Fleet DT Data Space Construction

Technology: In the face of the challenge of managing massive DT data, it has become a trend to establish an industrial data space. Typically, the DT data space comprises three layers: the perceptual layer, core layer, and application layer. At the perceptual layer, physical data and virtual model-related data are sensed and aggregated. The core layer associates and fuses all the DT data through data dictionaries and knowledge graphs. The service layer provides various services, such as data query, data visualization, and data generation, among others. This enables efficient management of the entire aero-engine fleet DT data.

(2) Aero-Engine Performance Data Generation Technology: Due to the complex nature of aero-engines operating under high temperature, high pressure, and high-speed conditions, certain parts cannot be equipped with sensors, and the data for some parts needs to be collected non-destructively. Simulation technology and DT models become effective methods for generating the required data. However, the generated data must be corrected and verified to ensure reliability and validity.

(3) Aero-Engine Fleet Multi-Level Data Fusion Technology: The DT of the aero-engine fleet involves massive amounts of heterogeneous data from multiple sources. However, using this data directly for aero-engine fleet maintenance without data fusion is challenging. Raw data is collected from multiple sensors, thus requiring spatiotemporal alignment and collaborative measurement. Extracted features from the raw data are associated with the operating conditions and states of aero-engine fleet maintenance through a sign matrix of heterogeneous data. Different data can lead to different conclusions for data-driven decision-making. Therefore, judgments should be

made based on the confidence and reliability of the conclusions derived from different data or characteristics, enabling the formulation of reasonable and credible decisions.

(4) Aero-Engine Fleet DT Data Servitization Technology: Data aggregation and data fusion serve as a fundamental guarantee for the application of aero-engine fleet DT data. However, in industrial scenarios, efficient utilization requires data servitization. This entails providing services and developing applications for data perception, storage, fusion, analysis, visualization, and more. By doing so, users in aero-engine fleet maintenance scenarios, including customers and operators, can utilize data in a simpler and more intuitive manner to optimize maintenance processes.

4 DT-enhanced aero-engine fleet collaborative maintenance operation mechanism

In response to the three inquiries raised in the previous article: *What is the current operating state of the aero-engine fleet? How to develop an aero-engine fleet maintenance plan? and How should the aero-engine fleet be specifically maintained?* It is necessary to clarify the operational mechanism and achieve the collaborative maintenance of the aero-engine fleet. Therefore, a proposed collaborative maintenance paradigm for the aero-engine fleet, as shown in Fig. 1, is based on the DT model and DT data. The aero-engine fleet collaborative maintenance operational mechanism can be divided into

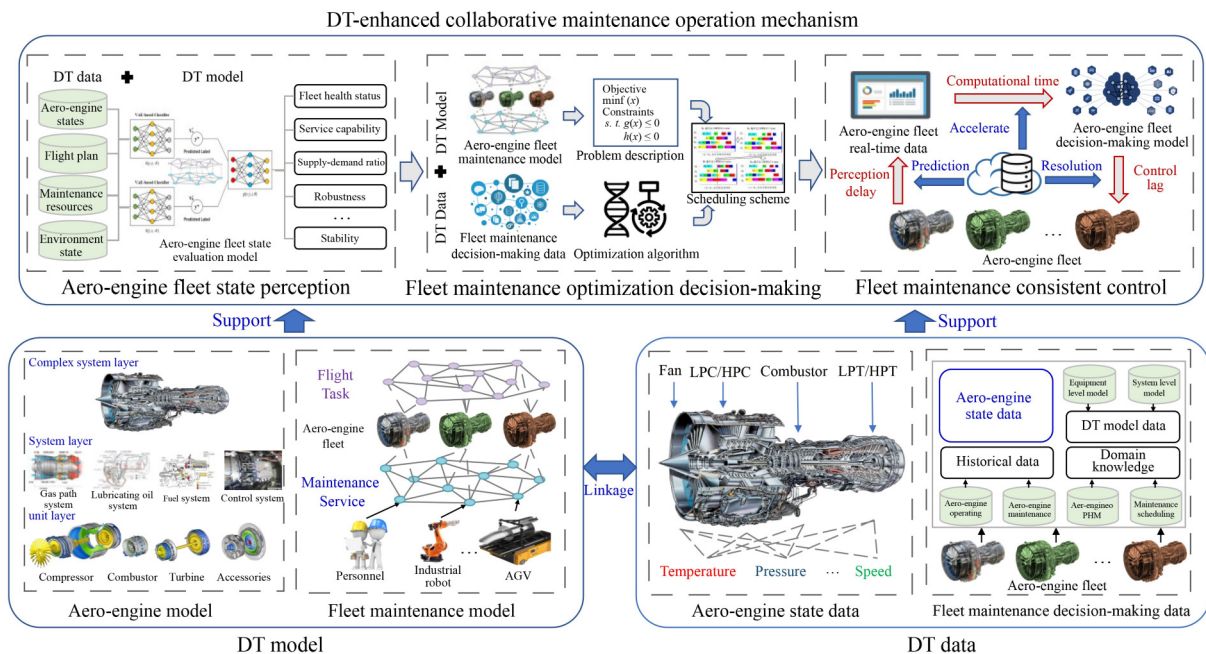


Fig. 1 DT-enhanced collaborative maintenance paradigm for aero-engine.

three parts: aero-engine fleet state perception, aero-engine fleet maintenance optimization decision-making, and aero-engine fleet maintenance interaction control.

(1) Aero-engine fleet state perception.

Addressing the first issue, perception of the fleet's state is essential. In the scenario of aero-engine fleet maintenance, there are various complex states. Therefore, perceiving and recognizing different states are the basic supports for fleet optimization decision-making and consistent interactive control of aero-engine fleet maintenance. Firstly, the performance and health state of the individual aero-engine and maintenance resources are extracted from the equipment-level DT model. Then, the aero-engine fleet state evaluation index system is established by comprehensively considering the performance, status, and relationships of various elements. This system involves various indexes such as fleet health status, flight plan load, maintenance service capability, robustness, stability, and more. Additionally, considering the system-level DT model based on complex network theory, typical characteristics of complex networks, such as degree distribution, average path length, and clustering coefficient, can be introduced as state evaluation indexes. All these indexes are obtained from the fusion of DT real-time data and the state evaluation model. On one hand, the aero-engine fleet DT state evaluation model incorporates corresponding DT data to evaluate the fleet's state. On the other hand, the fleet maintenance big data continuously deepens the understanding of the aero-engine fleet's state and iteratively updates the status evaluation model. Depending on the fused DT data and models, numerous different states are distinguished, which inevitably lead to different decision-making strategies and behaviors.

(2) Aero-engine fleet maintenance optimization decision-making.

In response to the second question, the optimization decision-making process for aero-engine fleet maintenance is essential. The traditional approach to aero-engine fleet maintenance decision-making is often based on the manager's personal experience, primarily focusing on individual engine maintenance decisions. However, by utilizing the available data and models of the aero-engine fleet, it becomes possible to carefully address the problem of system-level optimization decision-making for the fleet. Firstly, it is crucial to recognize that not all entities need to be involved in the decision-making process. Therefore, a selection of relevant entities should be made to address the decision-making problem effectively. Following this, utilizing the aero-engine fleet data and model, the current and predicted state of the fleet can be determined, and the corresponding objective function can be defined. For example, if maintenance tasks are urgent, efficiency becomes dominant in the objective function. On the other hand, if the maintenance tasks are not as

time-sensitive, the weight of cost and reliability in the objective function should be increased. Lastly, based on the current state of the aero-engine fleet, the decision-making mechanism can be adaptively adjusted using heuristic rules, intelligent optimization algorithms, machine learning methods, and other relevant approaches.

(3) Consistent interaction control for aero-engine fleet maintenance.

Although the DT model aims to provide an accurate representation of the physical space, errors may still arise due to model accuracy, information transmission, unknown disturbances, and other factors. In order to address the third question, ensuring consistency and achieving interactive control are crucial for implementing an optimal decision scheme in the physical space. Specifically, consistency includes three levels. First, virtual-real consistency refers to the alignment between the real-world physical space and the virtual model. For the DT model of an aero-engine fleet, it is necessary to continuously calculate model accuracy and calibrate model deviation parameters in real-time to ensure an accurate representation of the physical space. Second, data-model consistency refers to the coherence between DT data and corresponding DT models. The association mechanism between DT data and models is determined based on practical situations and physical laws, necessitating symbiotic evolution of both the data and models. Lastly, decision-behavior consistency pertains to the congruity between optimal decision and interaction control behaviors. It is therefore important to minimize controlling lag resulting from perception delay and computing time. Leveraging the DT data and models, the future state of the aero-engine fleet can be predicted to a certain extent. Based on this prediction, a compensation strategy for control lag can be devised. By addressing these three levels of consistency, the challenge of maintaining consistent interaction control in aero-engine fleet maintenance can be resolved.

5 Conclusions

With the advancement of the aviation industry and information technology, aero-engine maintenance has transitioned from single aero-engine maintenance to aero-engine fleet maintenance. In this paper, we propose a new framework for DT-enhanced collaborative maintenance of aero-engine fleets. However, while DT technology enhances aero-engine fleet maintenance, it also introduces new challenges, three of which have been discussed in this article.

Competing Interests The authors declare that they have no competing interests.

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