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A Review of Digital Twin for Vehicle Predictive Maintenance System

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Abstract

The development of Digital Twin (DT) has become popular. A dominant description of DT is that it is a software representation that mimics a physical object to portray its real-world performance and operating conditions of an asset. It uses near real-time data captured from the asset and enables proactive optimal operation decisions. There are many other definitions of DT, but not many explicit evaluations of DT performance found in literature. The authors have an interest to investigate and evaluate the quality and stability of appropriate DT techniques in real world aircraft Maintenance, Repair, and overhaul (MRO) activities. This paper reviews the origin of DT concept, the evolution and development of recent DT technologies. Examples of DTs in aircraft systems and transferable knowledge in related vehicle industries are collated. The paper contrasts the benefits and bottlenecks of the two categories of DT methods, Data-Driven (DDDT) and Model-Based (MBDT) models. The paper evaluates the applicability of the two models to represent vehicle system management. The authors present their methodological approach on Predictive Maintenance (PM) development basing on reliable DT models for vehicle systems. This paper contributes to design, operation, and support of aircraft/vehicle systems.

Introduction

Aviation is seen as technology-intensive because of the digital transformation that has been taking place throughout the industry for decades. This unveils an urgent need of effective, fast, and accurate data management and analysis method to ensure the sustainable reliability and safety of aircraft platforms throughout their lifecycles [1]. The connections between the physical asset and its digital version include information flows and data that includes physical sensor flows between the physical and virtual objects and environment.

There exist debates on what a DT is and how it benefits for aircraft cycle, from design, manufacture, to fleet-level management and individual aircraft operation monitoring and health management. The debates proposed different understandings of DTs. Some researchers believe that the DT research should focus on simulation. Some argue that the DT should contain three dimensions: physical, virtual and connection parts. Hence, two dominant categories of DTs then occurred, Data-Driven DT (DDDT) using simulation, and Model-Based DT (MBDT) implemented based on Hardware-in-loop (HIL) and physical-digital-physical loop.

Background

Physical Twin:

NASA's Apollo space program was the first program to use the "Twin" concept [2]. Two identical space vehicles were built in the program, so that the space vehicle on earth can mirror, simulate, and predict the conditions of the other one in space. The vehicle remained on earth was the twin of the vehicle that executed missions in the space.

Digital Twin

The concept and model of the DT was first publicly introduced in 2002 by Michael Grieves as a technique for Product Lifecycle Management (PLM) . Initially, DTs are recognized as an information system. The motivation of creating DTs is to develop a life-long asset information visualizing technique for asset-intensive industries. This is why a DT is described, in many research articles, as the virtual information integration of a physical asset. Then in 2012, the concept of DTs was revisited and further defined by the NASA as a multi-physics, multiscale, probabilistic, ultra-fidelity simulation that reflects, in a timely manner, the state of a corresponding twin based on the historical data, real-time sensor data, and physical model [2]. According to Gabor [3, 4], DTs can be multi-scaled simulations built based on the expert knowledge and real data collected from existing system, to realize a more accurate simulation and representation of the system. The DT integrates sensor data from the vehicle's on-board IVHM system, maintenance history and all available historical and fleet data. By combining this information, the DT continuously forecasts the health of the vehicle or system, the Remaining Useful Life and the probability of mission success.

Therefore, this paper aims at understanding DT technology, having sense of up-to-date research and applications in aviation and relevant manufacturing industries. This consolidates the basis for the author's research project on applying DT technology to flight control electrical actuator health management.

Evolution and Development

The need for an accurate and efficient health management system has become exceedingly important in safety-critical and mission-critical aerospace systems [5]. The most important goal of health management is to constantly monitor the performance of these aerospace systems, identify faults (diagnosis), predict possible failures in the near future, and quantify the Remaining Useful Life (RUL, prognosis) in order to aid online decision-making. These component-level mathematical models can be constructed either using laws of physics (physical-based models) or using data collected through component-level testing (data-driven models) and are used for both system-level diagnostics and prognostics.

Based on above discussion, it is clear that DTs have been extensively applied in the context of the Prognostics Health Management (PHM) techniques. Moreover, the DT-driven PHM shows great advantages over the traditional PHM methods in terms of four respects, i.e., model, data, interaction, and decision making. The traditional PHM mainly focuses on the geometric modeling and physical modeling, while it rarely considers the behavior modeling and rules modeling. As a result, the model cannot achieve high precision. In contrast, the DT-driven PHM can integrate the four dimensions of modeling to depict a practical situation more accurately. The ultra-fidelity can enhance the effectiveness of the PHM.

Data-Driven Digital Twin (DDDT)

A Data-Driven Digital Twin (DDDT) is a digital representation of a real-world system, process, or product that is powered by data and analytics. It is a virtual model of a physical entity that is constantly updated with real-time data from sensors and other sources. The goal of a DDDT is to provide a virtual replica of the real-world entity that can be used for a variety of purposes, such as monitoring, prediction, optimization, and simulation. By constantly updating the DDDT with real-time data, organizations can gain a better understanding of the performance and behavior of their systems and use this information to make data-driven decisions and improvements.

Model-Based Digital Twin (MBDT)

A Model-Based Digital Twin (MBDT), on the other hand, is a digital representation of a real-world system or process that is based on a mathematical or computational model. It is a virtual replica of the real-world system that is built using principles of physics, engineering, or other scientific disciplines. The goal of a MBDT is to simulate and predict the behavior of the real-world system in order to optimize its performance, improve efficiency, and reduce costs. By building a virtual model of the real-world system, organizations can test and optimize different scenarios and configurations to identify the best course of action. This can help organizations make more informed and accurate decisions and improve the efficiency and performance of their operations.

One key difference between DDDT and MBDT is the source of the data used to build and update the DTs. A DDDT is powered by real-time data from sensors and other sources, whereas a MBDT is based on a mathematical or computational model. This means that a DDDT is constantly updated with new data, while a MBDT relies on the accuracy and validity of the underlying model.

Another difference is the level of complexity and detail that can be captured by the DTs. A DDDT is able to capture more detailed and granular data, as it is based on real-time measurements from sensors and other sources. This can make it more accurate and useful for predictive and optimizing the performance of complex systems and processes. However, a MBDT may be more suitable for simulating and optimizing the performance of simpler systems or processes, as it relies on a computational model that may be easier to build and maintain. Ultimately, the choice between a DDDT and MBDT will depend on the specific needs and goals of the organization.

DT Application in Industries

DT for Aircraft

DT application for aircraft can be split into multiple categories by levels of application scenarios.

For aircraft maintenance perspective, DT-based Predictive Maintenance (PM) can significantly add value to condition-based Maintenance under the Integrated Vehicle Health Management (IVHM) by offering data supporting normal, degradation and abnormal operations [6].

For aircraft system operation recurrence DTs, Li *et al.* [7] proposed a concept developing a prognostics DT based a dynamic Bayesian network to monitor health status of aircraft wings. Seshadri and Krishnamurthy [8] focused on structure status monitoring and health assessment management and developed a DT-based Structural Health Management (SHM) tools, which enables accurate detection. It also provides a foundation to employ on-board and in-flight condition monitoring and prognostics. Tuegel [9] also assessed an Airframe Digital Twin in assisting of designing and maintaining airframes. Xu *et al.* [10] proposed a DT-driven analysis framework for optimizing gas exchange system of 2-stoke heavy fuel aircraft engine. Within this DT framework, multiple modules interact with their targeted physical entities of engines and work collaboratively within the group.

DT for Manufacturing Industries

Modern manufacturing requires physical and digital interaction in a closed-loop manner and the digitalization of manufacturing systems consolidate the basis of smart manufacturing [11]. Manufacturing is treated as one of the most encouraging industries where the DTs may be successfully applied for solid benefits in terms of maintenance and operations monitoring and optimization [12]. As discussed by Kritzinger *et al.* [13], the DT can help simulate and optimize the production system, from single components to whole assembly. In detail, DTs support production planning, control, and maintenance, as well as manufacturing platform layout planning to gain increased competitiveness, productivity and efficiency. A lot of new concepts and proposals are being adapted to manufacturing phase.

At product level, process monitoring, and virtual modeling are aspects addressing researchers' attention. Zheng *et al.* [14] established a three-layer DT model for geometric feature inspection of car body-in-white. The environmental consists of a DT workshop layout as data object and source controller, a DT real-time mapping module as data collector and simulator, and a DT pattern recognition module as data transformer and demonstrator. Botkina *et al.* [15] developed a DT of a cutting tool by collecting data throughout the production lifecycle. The data format and structure, information flows between physical tool object and the DT assets are main aspects the authors focused on. Zhang *et al.* [16] applied a DT-based solution to the hollow glass production line by merging, transforming and distributing real-time data to generate an authoritative DT model.

At the level of manufacturing platform, Tao and Zhang [17] proposed a virtual shop-floor concept by establishing a DT expanding its four key components: physical shop-floor, virtual shop-floor, shop-floor service system, and shop-floor DT data.

Discussion

The development of DT now has become prosperous in various industries as discussed. While it helps to shape a "better" or "way" to develop DTs by understanding both benefits and shortcomings that current DTs face. In this section, the authors discussed about pros and cons DTs equip in multiple levels of operations within the aviation domain.

Pros

Improved decision-making and optimization. Another main advantage of DTs is that it allows organizations to make more informed and accurate decisions. By constantly updating the DT with real-time data from sensors and other sources, organizations can gain a better understanding of the performance and behaviour of their systems, processes, and products. This information can be used to optimize operations, identify inefficiencies, and make data-driven decisions that improve the overall performance of the real-world entity. Virtual test platform helps accelerate verification and validation process and take down the overall time consumption of development cycles.

Improved maintenance and repair. As a critical potential solution and trend of implemented PM technique, it benefits with its ability to improve maintenance and repair processes. By using a DT to monitor the performance and condition of aircraft systems and components, OEMs, airlines, or third-party operators can identify potential issues and schedule maintenance before problems occur. This can help reduce downtime and improve the reliability of aircraft, leading to increased customer satisfaction and lower costs for operators. For example, as discussed in application section, DTs can be employed to monitor the wear and tear of aircraft engines, identifying potential issues and scheduling maintenance before a failure occurs. This can help reduce the risk of unexpected engine failures and improve the overall reliability of the aircraft.

Enhanced safety and risk management. Similarly, DTs can also trigger the improvement of safety and risk management in aviation by constantly monitoring the performance and condition of aircraft systems and components. Operators can then identify potential safety issue and take proactive measures to prevent accidents and incidents. DTs can also assist on improving risk management by predicting and mitigating the impact of potential disruption, such as weather events or equipment failures.

DTs also show advantages in aircraft/aircraft fleet operations. **Optimized flight operations** can be achieved by applying DTs. By using a DT to monitor and analyze data on flight routes, fuel consumption, weather patterns, and other factors, operators can identify opportunities to reduce costs and improve efficiency. Other aspects of flight operations, such as crew scheduling, aircraft utilization, and passenger experience are also worth researching on.

Also, thanks to the real-time information fed to the aircraft, it helps **improve customer experience**. Operators can modify front-end passenger experience based on DTs-provided information. Another potential solution to enhance customer experience is to understand one customer from pre-flight to after-flight. For example, a DT can be used to track and analyze data on passenger preferences and needs, allowing airlines to tailor their products and services to individual customers.

Cons

Aircraft safety redundancy is one of essential factors that regulate the design, development, and implementation of aircraft systems. It criticizes the employment of new techniques by challenging in several aspects. However, the representability of DTs to one aircraft subsystem and compatibility between DT and developing-PM techniques for such asset are rarely addressed in literature.

Data quality and accuracy is another potential challenge of DTs for PM. In order to be effective, DTs must be powered by high-quality data that accurately reflects the performance and condition of the real-world system or equipment. If the data is inaccurate or unreliable, DT may provide misleading or incorrect predictions, leading to incorrect maintenance decision, which can have serious consequences, such as component failures or downtime. Ensuring the quality and accuracy of the data used to build and update DTs is therefore critical to its effectiveness. According to Badea *et al.* [18], an average Boeing 737 can generate 40 terabytes of information per hour, given the operation under six-hour flight between 2 cities. Therefore, further studies are needed on big data management.

Urgent need of underlying-data management for collaborative interaction and association. The lack of data standardization across different systems and equipment is always a concern among data-related technology. In order to be effective, DT mush be able to integrate and analyze data from a wide range of sources, including sensors, maintenance records, and other data sources. However, the data generated by different systems and equipment may be structured and formatted differently, making it difficult to integrate and analyze. To overcome this challenge, organizations may need to invest in data standardization and integration technologies to ensure that data from different sources can be effectively analyzed and used by DTs. Abdallah and Fan [19] proposed an ontology knowledge management concept can support full digitization in aircraft operations and maintenance.

High upfront costs. Building and maintaining a DT requires significant investment in hardware, software, and data analytics capabilities, especially for large, complex systems with many components, e.g., ECS and propulsion systems. This can be a significant burden for organizations with limited resources and may require a long-term commitment in order to see a return on investment. In addition, organizations must also consider the complexity of the real-world system or components being represented by DTs, as well as the complexity of the data sources and analytics tools being used. This can make it difficult for organizations to effectively implement and maintain a DT for PM.

DDDT Framework for Electrical Actuation PM

This paper set up the basis of the authors' research on applied PM methodology approach. A DDDT framework is proposed as a PM method (Figure 1). Two simulation models are developed to represent different Electrical Actuation (EA) systems and generating data. Multiple-step data analyses are applied. For chosen features, value of normal operational data status or natural index can be used as reference or threshold value.

In Phase I of the framework development, the lack of open-sourced dataset and the limited access to practical and historical operational data of two EA systems, Electro-Mechanical Actuator (EMA) and Electro-Hydro-Static Actuator (EHSA), the authors decided to develop two simulation models as data generators to represent the two EAs. In Phase II, a DDDT Framework was proposed by combining the two models and algorithms, including data-applied pre-processing, feature-extracting, threshold-injecting algorithms. In

Phase III, the author aims at accessing data for the framework's validation and verification.

In terms of the accuracy, precision and granularity, or how the two models can highly represent real assets, the author started from understanding failure characteristics of the two EAs at subsystem and component levels. Referring to handbooks and natural index of machines and machineries, it forms a solid basis for the development and implementation of models and the framework, shown as Figure 2 [20].

The framework can contribute to:

1) Reliable data generator for further research.
2) Establish failure and fault library base on outcomes.
3) Real-time health monitoring and improve precision and accuracy in RUL estimation.

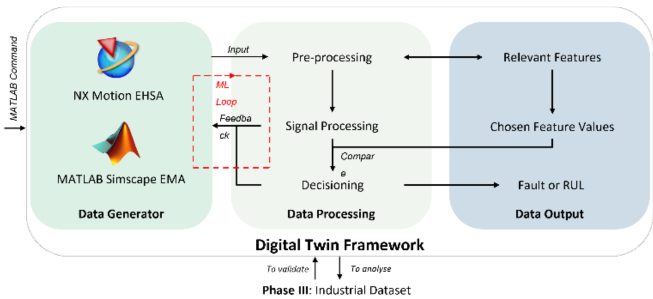

Figure 1 A DDDT Framework for Electrical Actuation PM and Prognostics Proposal.

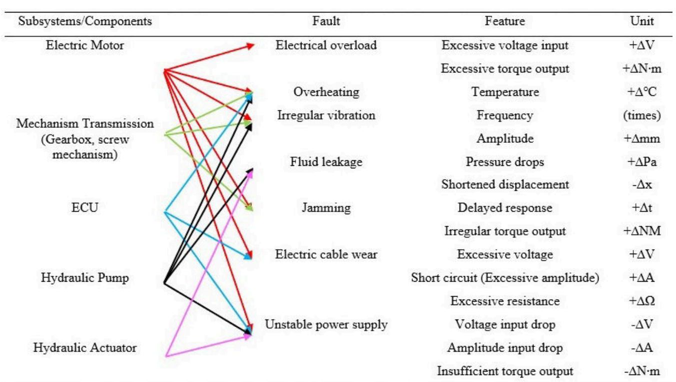

Figure 2 Fault-Feature-Index Matrix of a fault/failure EA system at component level [20].

Conclusion

This paper discussed Digital Twin technique proposed in research and industrial applications:

1) DT has become an ongoing trend to transfer exist dataset to a digital replica of a physical asset in several industries and contexts.
2) An understanding of two dominant DTs, DDDT and MBDT has been illustrated. A comparison of the two methods is conducted. This consolidates the author's next phase plan of building up a DDDT for Flight Control electrical actuator prognostics method.
3) Research activities and industrial applications involved DT are discussed. The outcomes imply the DT has huge potential in getting mature in data capturing, transforming and operation/production recurrence.
4) Pros and cons of DT applied to aircraft maintenance and aircraft operations are detailed discussed.
5) A briefing about the authors proposed a DDDT framework for electrical actuation health management and prognostics is provided.

These helps the author design the DDDT framework and develop simulation scenarios in a reliable way. The validated DT model will be used to support PM for flight control electrical actuation system health management.

References

1. Li, L., Aslam, S., Wileman, A., Perinpanayagam, S., "Digital Twin in Aerospace Industry: A Gentle Introduction," in *IEEE Access*, DOI: 10.1109/ACCESS.2021.3136458.
2. Glaessgen, E.H., Stargel, D.S., "The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles," *53rd Structure Dynamics, and Materials Conference,* 2012.
3. Gabor, T., Belzner, L., Kiermeier, M., Beck, M.T., Neitz, A., et al, "A Simulation-Based Architecture for Smart Cyber-Physical Systems," in *IEEE International Conference Autonomic Computing*, July 2016.
4. Falekas, G., Karlis, A., "Digital Twin in Electrical Machine Control and Predictive Maintenance: State-of-the-Art and Future Prospects" in *Energies*, 2021, 14, 5933. DOI: 10.3390/en14185933.
5. Sankararaman, S., Daigle, M., Saxene, A., Goebel, K., "Analytical Algorithms to Quantify the Uncertainty in Remaining Useful Life Prediction,", *2013 IEEE Aerospace Conference,* DOI: 10.1109/AERO.2013/6496971.
6. Xiong, M., Wang, H., "Digital Twin Applications in Aviation Industry: A Review," in the *International Journal of Advanced Manufacturing Technology*, 2022, pp. 5677-5692, DOI: 10.1007/s00170-022-09717-9.
7. Li, C., Mahadevan, S., Ling, Y., Choze, S., Wang, L., "Dynamic Bayesian Network for Aircraft Wing Health Monitoring Digital Twin," in *AIAA Journal*, vol. 55, No. 3, 2017, DOI: 10.2541/1.J055201.
8. Seshadri, B.R., Krishnamurthy T., "Structural Health Management of Damage Aircraft Structures Using the Digital Twin Concept," in *AIAA SciTech Forum, 25th AIAA/AHS Adaptive Structures Conference,* p. 1675, 2017.
9. Tuegel, E.J., "The Airframe Digital Twin: Some Challenges to Realization," in *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference,* 2012.
10. Xu, Z., Ji, F., Ding, S., Zhao, Y., Zhou, Y., *et al.*, "Digital Twin-Driven Optimization of Gas Exchange System of 2-Stroke Heavy Fuel Aircraft Engine," in *Journal of Manufacturing Systems*, vol. 58, pp. 132-145, DOI: 10.1016/j.jmsy.2020.08.002.
11. Shao, G., Helo, M., "Framework for a Digital Twin in Manufacturing: Scope and Requirements," in *Manufacturing Letters*, DOI: 10.1016/j.mfglet.2020.04.004.
12. Cimano, C., Negri, E., Fumagalli, L., "Review of Digital Twin Applications in Manufacturing," in *Computers in Industry*, 113 (2019), DOI: 10.1016/j.compind.2019.103130.
13. Kritzinger, W., Karner, M., Traar G., Henjes, J., Sihn, W., "Digital Twin in Manufacturing: A Categorical Literature Review and Classification," in *International Federation of*

Automatic Controls, 51-11(2019), 1016-1022, DOI: 10.1016/j.ifacol.2018.08.474.
14. Zheng, Y., Chen, L., Lu, X., Sen, Y., et al., "Digital Twin for Geometric Feature Online Inspection System for Car Body-in-white," in *International Journal of Computer Integrated Manufacturing*, 34:7-8, 752-763, DOI: 10.1080/0951192X.2020.1736637.
15. Botkina, D., Hedlind, M., Olsson, B., Henser, J., Lundholm, T., "Digital Twin of a Cutting Tool," in *51st CIRP Conference on Manufacturing Systems,* DOI: 10.1016/j.procir.2018.03.178.
16. Zhang H., Liu, Q., Chen, X., Zhang, D., Leng, J., "A Digital Twin-Based Approach for Designing and Multi-Objective Optimization of Hollow Glass Production Line," in *IEEE Access*, vol. 5, pp. 26901-26911, 2017, DOI: 10.1109/ACCESS.2017.2766453.
17. Tao, F., Zhang, M., "Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing," in *IEEE Access*, vol. 5, pp. 20418-20427, 2017, DOI: 10.1109/ACCESS.2017.2756069.
18. Badea, V.E., Zamfiroiu, A., Boncea, R., "Big data in the Aerospace Industry" in *Informatica*, Econimica, Vol. 22. DOI: 10.12948/issn14531305/22.1.2018.02.
19. Abdallah, A.A., Fan, I.S., "Emerging Challenges of Digital Aircraft Operations and Maintenance: A Knowledge Management Perspective", *9th International Conference on Through-life Engineering Services*, Cranfield University, 3-4 November, 2020.
20. Wang, C., Fan, I.S., King, S., "Failure Mapping for Aircraft Electrical Actuation System Health Management," in *PHM Society European Conference*, 7(1), pp. 509-520, DOI: 10.36001/phme.2022.v7i1.3354.

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Definitions/Abbreviations

DT	Digital Twin
DDDT	Data-Driven Digital Twin
MBDT	Model-Based Digital Twin
HIL	Hardware-In-Loop
PLM	Product Lifecycle Management
PM	Predictive Maintenance
IVHM	Integrated Vehicle Health Management
SHM	Structural Health Management
ECS	Environmental Control System
EA	Electrical Actuator
EMA	Electromechanical Actuator
EHSA	Electrohydrostatic Actuator

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