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The Role of Data Fusion in Predictive Maintenance Using Digital Twin

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Abstract. Modern aerospace industry is migrating from reactive to proactive and predictive maintenance to increase platform operational availability and efficiency, extend its useful life cycle and reduce its life cycle cost. Multiphysics modeling together with data-driven analytics generate a new paradigm called "Digital Twin." The digital twin is actually a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information, and can forecast the future of the corresponding physical counterpart. This paper reviews the overall framework to develop a digital twin coupled with the industrial Internet of Things technology to advance aerospace platforms autonomy. Data fusion techniques particularly play a significant role in the digital twin framework. The flow of information from raw data to high-level decision making is propelled by sensor-to-sensor, sensor-to-model, and model-to-model fusion. This paper further discusses and identifies the role of data fusion in the digital twin framework for aircraft predictive maintenance.

INTRODUCTION

According to [1], 42% of delayed flights are caused primarily by airline processes, such as maintenance. Airlines want better maintenance, repair, and overhaul (MRO) performance and improved quality, cost, and turnaround times within budget and schedule. Today's MRO and in-service support (ISS) functions are facing challenges on several fronts, from slow turnaround time and poor data integrity to aging systems and outdated manual processes. Meanwhile, the MRO market is expanding and its growth is anticipated to have a big impact on the future of aircraft maintenance. To address these challenges for MRO, new technologies with powerful capabilities are needed to help make faster and more informed decisions for optimal maintenance avoiding any catastrophic failure.

An exciting chance to address this need is coming with the fourth industrial revolution triggered by new informa- tion and communication technology (ICT) and data-intensive methodologies (i.e., artificial intelligence and big data techniques). Internet Protocol version 6 (IPv6) is the most recent version of the Internet protocol, which provides practically unlimited IP addresses. IPv6 enables the "Internet of Things (IoT)" to happen as anything with an IP address can be connected through the Internet. The IoT brings together sensors, cloud computing, and big data analytics and will profoundly transform our society to a digital world. Industrial IoT, also known as IIoT, is the use of IoT technolo- gies in industrial applications where robustness, reliability, and security are highly desired performance requirements for IIoT. For aviation, the direct economic impact from IIoT is the implementation of predictive maintenance, which will turn the aggregated data and information into actionable decisions for aircraft maintenance. The predictive main- tenance has the capability to determine when maintenance should be performed based on the actual conditions of aircraft structures, components, and sub-systems. Once in place, predictive maintenance capabilities could eliminate

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added expenses such as expedited shipping costs for parts or supplies, reduce overtime expenses for crews and, most importantly, lead to fewer unplanned maintenance downtime events [2].

The "digital twin" is a disruptive technology that creates a living model of a physical asset for predictive maintenance. The living model will continually adapt to changes in the environment or operation using real-time sensory data and can forecast the future of the corresponding physical assets [3]. A digital twin can be used to proactively identify potential issues with its real physical counterpart. It allows the prediction of the remaining useful life (RUL) of the physical twin by leveraging a combination of physics-based (physics from first principles) models and data-driven analytics.

The digital twin ecosystem comprises the sensor and measurement technologies, industrial Internet of Things, simulation and modeling, and machine learning. From the computational perspective, the key technology to propel a digital twin is the "data and information fusion," which facilitates the flow of information from raw sensory data to high-level understanding and insights. The digital twin generally incorporates three-level fusion, e.g. signal-, feature-, and decision-level fusion, into its computational framework. At each implementation level, the data-information fusion technologies contribute to high-quality signals, distinctive features, and optimal decisions. This paper identifies the role of data-information fusion in the implementation of digital twin for aircraft predictive maintenance and MRO-ISS business. The impact of industry digital transformation on MRO-ISS is analyzed and discussed. The technology trends are also highlighted.

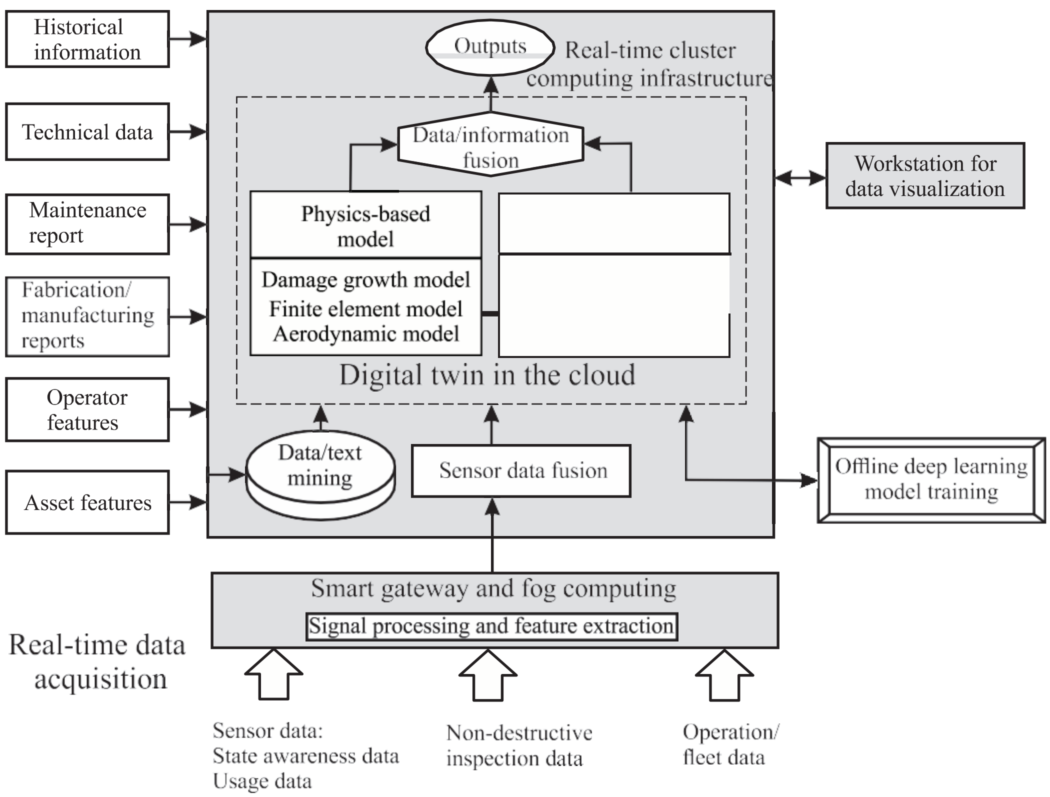

FIGURE 1. The system architecture of digital twin ecosystem.

DIGITAL TWIN FOR MRO APPLICATIONS

A definition of digital twin is "*An integrated multiphysics, multiscale, probabilistic simulation of an as-built system, enabled by digital thread, that uses the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin*" [4]. The overall architecture of a digital twin ecosystem is illustrated in Fig. 1. The key functionality of digital twin is implemented through physics-based models and data-driven analytics to provide accurate operational pictures of the assets [5]. Thus, the digital twin can mirror the activities of its corresponding physical twin with the capabilities of early warning, anomaly detection, prediction and optimization.

The industrial Internet of Things system carries out the real-time data acquisition through its smart gateway and edge computing devices. The pre-processed online sensory data will then be fused to feed the digital twin model. The offline data will be processed with text/data mining algorithms and then inputted to the digital twin model as well. The offline computing resources can be utilized to train the deep learning models used by the digital twin. The digital twin combines modeling and analytics techniques to create a model of a specific target, e.g., flight-critical component, and derive an actionable outcome from the model. These insights can be obtained by fusing the outputs from physics-based models and data-driven analytics. Then, the digital twin will be used in a specified predictive maintenance workflow to enable the delivery of accurate forecasting, using the data that is continuously acquired with the IIoT system.

New technology aircrafts will generate terabytes of data from a cross-country flight with onboard sensors [6]. How to benefit from using these data to maintain these aircrafts remains a topic for MRO-ISS industry. Currently, the aerospace industry is moving from reactive to proactive maintenance for the purpose of reducing maintenance costs, operational downtime, and capital investment by extending the useful life of aircraft components. The aerospace industry has requested advanced analytics coupled with industrial IoT to achieve these objectives. The essential technologies are integrated into the digital twin ecosystem for the MRO applications.

ROLE OF DATA FUSION IN THE DIGITAL TWIN ECOSYSTEM

The data fusion techniques were applied to non-destructive evaluation years ago [7, 8, 9], while the research on data fusion has a much longer history [10]. The more general concept of "information fusion" is defined as "*the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making*." [11]. In this paper, we use the term "data fusion" to refer to data and information fusion.

The role of data fusion in the digital twin ecosystem is illustrated in Fig. 3. The core elements of a digital twin's "multiphysics, multiscale, and probabilistic simulation" are implemented by the physics-based models and data-driven models. The source of information can be treated as a "sensor," either a "hard" sensor or a "soft" sensor. The potential of data fusion operations are identified from Fig. 2 [12]. The benefits of the fusion operations are listed as follows:

1. Sensor fusion – better signal quality
2. Physics model fusion – better model performance
3. Data model fusion – better model performance
4. Sensor and physics-based model fusion – adaptive physics-based model
5. Sensor and data model fusion – robust data-driven model
6. Physics and data model fusion – improved prediction
7. Sensor, physics, and data model fusion – reliable decision making

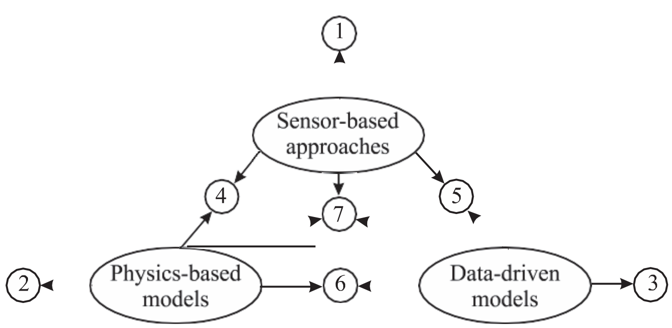

FIGURE 2. Possible fusion operations in digital twin development.

Data are collected through aircraft onboard sensors and offline non-destructive inspection (NDI). The offline inspection data should be made available online as a reference or baseline for monitoring sensors. The raw data can be collected and processed with the "fog" or "edge" computing devices [13]. The NDI could serve as the baseline while the online sensors will monitor the working status and loads. The *signal-level* fusion will be conducted to achieve a better signal with higher SNR or fidelity for further processing or interpreting while the data will be put into the historical records for future use. The sensory data and signals are often employed by physics or data models for model updating [14]. All the models need to be adaptive to the changing environment. The fused sensor data or extracted features will be fed into the models for prediction.

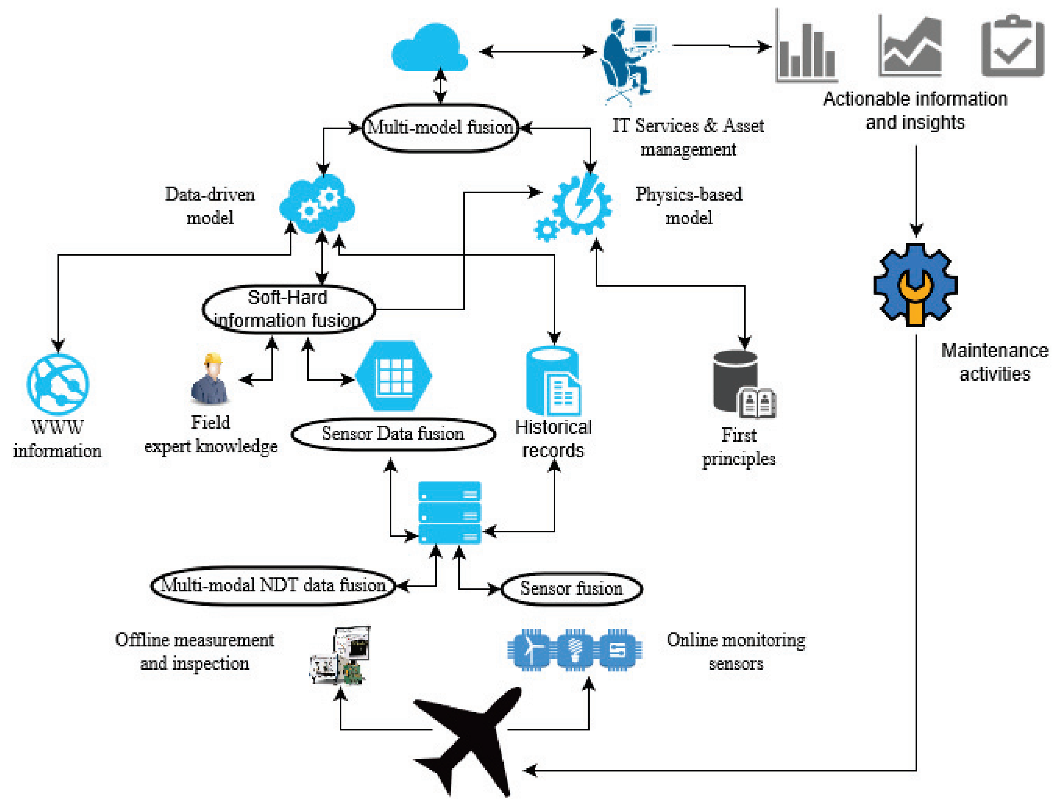

FIGURE 3. The role of data fusion in the digital twin framework.

Domain knowledge and experience are valuable for condition assessment and diagnoses. Incorporating human knowledge into the data-driven model should be accomplished by the "soft" and "hard" data fusion [15]. Modeling human knowledge still remains a topic for research community, e.g., human-centered computing [16]. The popular solutions include fuzzy inference, case-based reasoning, and ontology-based approaches [17, 16, 18]. The ontology uses classes, properties, and instances to represent the terms and relations among specific knowledge [17]. This modeling method can provide common semantic and query heterogeneous databases [17]. The ontologies have been applied to information fusion [19, 20]. Web-based technologies also enable the retrieving, analyzing, and processing relevant information online [21, 22] and could provide another source of information or tool for the digital twin ecosystem. Data-driven modeling is propelled with recent advances in machine learning and artificial intelligence. It exclusively relies on the data directly or indirectly related to the target object. Upon the availability of historical data, it is possible to train a comprehensive model to predict the remaining useful life (RUL) of the flight-critical components or subsystems. The data-driven models can be used for diagnosis and prognosis. The performance can be further enhanced through the ensemble and fusion of multiple individual models [23]. Thanks to the capability offered by IIoT for acquiring a large amount of relevant data, the data fusion will also evolute into evidence-driven or learning-based approaches for big data sets from the classic methods, such as Bayesian inference and Dempster-Shafer reasoning.

Physics-based models are based on the first principles of physics. This depends on the physical processes involved, e.g., damage growth or an aerodynamic application. Due to the limited knowledge of our human beings on a complex mechanism, individual or even multiple models can only partially simulate the overall process. Multiple models need to run in parallel to reflect the varied aspects of a physical mechanism of interest. The physics-based models also receive inputs from acquired measurement and sensory data from the fog/edge computing to adapt the models to the dynamic environment. Both the data-driven models and physics-based models are running in a cloud computing environment as the cloud is the place to centralize and process all the pre-processed data from fog/edge computing devices.

Both the data-driven and physics-based models output the prediction of remaining useful life (RUL), which can be used in the following decision-making process. Knowledge of the RUL will enable an efficient maintenance schedule by avoiding any unpredicted system shutdowns [24]. Complementing each other, the two types of modeling need to be fused for more accurate and reliable prediction [25]. The decision will be made based on the multi-model fusion outcomes. The action will be taken based on the derived evidence. The future MRO can be performed based on the risk estimated from the RUL accordingly.

TRENDS FOR TECHNOLOGY DEVELOPMENT

Towards the future digital twin ecosystem, the technologies also evolve with the advances of the "information and communication technology" (ICT) as well as the revolution initiated by Industrial 4.0. One field is the non-destructive testing. There are a number of trends for future non-destructive testing (NDT):

- Implement real-time and flexible NDT with modern ICT;
- Integrate NDT into manufacturing process through online monitoring;
- Achieve decision making in NDT services.

Conventional NDI is usually conducted offline manually. The real-time digital technology makes the NDT results available in a timely manner. The current innovations available on the market include the USB-based devices, which can stream inspection data to central data repository in real time [26, 27]. This change makes it possible to manage and store NDI data online. More importantly, the historical inspection data become available. The "mixed reality" technology, such as Microsoft HoloLens, can be applied to visualization in digital twin as well as implement remotely supervised inspection. 3D model is critical for digital twin development. Modern technologies enable precision scanning of parts and components with laser and camera based vision technology [28]. This technology will make the 3D model of existing components available, which were not manufactured digitally. While sensors for online monitoring are being actively developed, the conventional NDT has well-established standards and performance metrics, i.e., probability of detection. Replacing NDT with online sensors will not happen by tomorrow, but the convergence of these two technologies will be the future. Decision making is the objective of digital twin, and NDT is an essential tool to achieve such objective.

SUMMARY

This paper briefly describes and reviews the digital twin technology for aircraft maintenance, repair, and overhaul. The digital twin ecosystem integrates the modeling and simulation while taking advantage of the industrial Internet of Things for data acquisition and information processing with cloud computing. The focus is on the role of data fusion in the digital twin development. The data fusion also evolves with the advances of ICT and deal with increasing data in terms of its volume, velocity, and variety. The flow of information from raw data to high-level understanding is propelled by data fusion techniques, which are implemented and will function at different levels. In addition, the technology advances and requirements also have a great impact on the conventional industry such as non-destructive testing. All the technology advances will change the future MRO business in the aerospace industry.

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