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Procedia CIRP 96 (2021) 163–168

www.elsevier.com/locate/procedia

CIRPe 2020 – 8th CIRP Global Web Conference – Flexible Mass Customisation

Towards Information Management Framework for Digital Twin in Aircraft Manufacturing

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Abstract

Aircraft manufacturing industries often evolve in the ecosystem of complex designs and manufacturing processes associated with large volume of information generated along the lifecycle. Digital Twin (DT) technology has the potential of leveraging such information to provide useful insights benefiting the overall business in many ways. Information Management (IM) for DT is still an ongoing challenge for many industries, thus leaving a considerable research gap. In this paper, an IM framework for DT in the aircraft manufacturing sector is proposed. The key phases and elements of IM are discussed on which the framework is constructed. The potential application of the framework along aircraft lifecycle is further discussed. The framework not only provides an effective approach to managing information but also opens new research prospects in DT domain.

Keywords: Digital Twin (DT), Aircraft Manufacturing, Information Management (IM)

1. Introduction

Digital Twin (DT) is the combination of logically integrated models of a physical asset to give useful insights using data and information associated with those models. The concept of DT has been introduced by Grieves at the University of Michigan in 2002 [1] refereeing it as the conceptual ideal for the Product Lifecycle Management (PLM). DT is predicted to play a significant role in improving consistency, seamless development process and the possibility of reuse in subsequent stages along the product lifecycle [2]. As DT allows the integration of end-to-end information between both physical and virtual spaces, Information Management (IM) becomes the key essential activity for DT development and implementation process irrespective of the application. IM becomes even a bigger challenge whilst leveraging DT in complex aircraft manufacturing industries. Aircraft lifecycle includes complex design, manufacturing process, long testing & certification process and safety-critical operational life. Therefore, to harness technology like DT, IM becomes crucial for effectively manage data and information across the enterprise. The existing literature mainly focuses on DT development for individual and standalone systems, thus lacking a holistic IM approach to DT.

In this paper, a novel IM framework is proposed dedicated to the aircraft manufacturing industry. The paper covers the current state of managing an asset in an industrial space. Further, the key phases of IM and information flow for DT across aircraft manufacturing industry are discussed based on which the framework is proposed. Through a case study, a potential application and benefits of the framework are explained. The research is in collaboration with the industrial partner which is one of the leading aircraft manufacturing company globally.

10.1016/j.procir.2021.01.070

Nomenclature

DT	Digital Twin
IM	Information Management
IoT	Internet of Things
PLM	Product Lifecycle Management
PDM	Product Data Management
DMU	Digital Mock-Up

2. Digital Twin (DT) & Information Management (IM)

As a product, aircraft and its systems are designed, developed and maintained for the long-term sustainment. The average airline lifespan for a single-aisle aircraft is around 25-30 years with adequate periodic maintenance checks [3]. Maintaining such systems for long-term sustainment needs dedicated IM infrastructure and tools. DT for such systems would also require maintainability of information. Aircraft manufacturing industry manages a large amount of data with tools such as PLM & PDM (Product Data Management) and simulation-based tools. The systems like PLM and PDM store and release huge amount to product/process data coming from multiple authorising tools and sources [2]. As DT is heavily driven by information across the asset or system, IM becomes one of the key aspects to support multiple services-based business models, maintainability of information and long-term system sustainment.

Only a few research works focus on the information and data side of DT. John [4] proposed DT design framework using ontologies for data capturing in complex engineering systems. Gulnar [5] used ontologies for querying data and semantically integrate knowledge base to facilitate intelligent diagnostics of an industrial turbine. Agniva [6] proposed a way of formalising knowledge as DT models coming from sensors of industrial production lines. This approach uses a Graph-based Query Language (GQL) equivalent to conjunctive queries and has been enriched by inference rules. In both cases, the use of a single semantic definition for DT is not well explored.

Looking at the DT data management side, Zhang [7] proposed an approach to design and develop DT of production line based on semantic data model as a reference model and synchronisation of equipment at the physical level. Angrish [8] introduced an architecture based on databases and generic machine access library for the virtualisation of the production factories. Uhlemann [9] proposed a multi-model data acquisition approach to minimise the delay between the time of data acquisition and creation of production process DT. Requirements driven approach to DT is also proposed [10]. For a concept like DT, understanding the context of data is important and asking the right questions to make sense out of that data. The freshness and completeness of data, merging of structured and unstructured data is still an ongoing challenge for DT. Therefore the existing framework targets to address the following research gaps:

- requirements for DT development based on specific views along the aircraft lifecycle;
- research in data modelling and data structuring for DT;
- integrated framework for IM for DT in aircraft manufacturing domain

3. DT IM Framework

3.1. Challenges

DT has the ability of real-time control and optimisation of product and production lines in manufacturing environments [11], but the cost of developing and maintaining DT must be driven by both business and economic models of the industry. Not only cost but maintaining DT along its lifecycle is challenging in multiple aspects. The challenges of DT have been summarised [12]. The proposed IM framework is targeting to address some of the following challenges in the aircraft manufacturing industry:

3.1.1. Big data - variety & volume

Big data involves the collection of datasets that are so large and complex that it becomes difficult to process using hands-on database management tools or traditional data processing applications. The amount of data generated across aircraft lifecycle is immense and industries often find it difficult to utilise it via technologies such as DT. The current research lacks an effective approach for resolving implications of big data on DT across an enterprise.

3.1.2. Information sharing

The information sharing can be segmented into two: internal data sharing and external data sharing [12]. Information sharing across the value chain brings tangible benefits and transparency but still remain an ongoing challenge due to silo effects. Therefore, information sharing becomes a serious challenge beyond the technology and engineering complexities for DT.

3.1.3. Information organisation

Out of a large amount of information, organisation of information is also an ongoing challenge in aerospace and aircraft manufacturing domain. With sector servitisation, data-driven solutions are desirable. Such solutions often lead to more data and information to be organised and maintained across the process. Therefore, for a concept like DT, organisation of information remain a challenge.

3.1.4. Scalability

For DT, designing the virtual copies of the physical assets and manufacturing processes, scalability is one of the important model properties [7]. Scalability varies with different architectures, data load, and ability to change the level of parameters, supply chain complexity and computational ability. For all these elements, scalability tends to be the key issue for DT [13]. A robust and flexible IM approach is a way to address scalability issues.

3.2. Asset management

The asset management domain is widely known for leveraging DT technology [14]. The current process of managing an asset involves different phases of information flow. The digital flow of the traditional asset management process is conceptualised and explained, as shown in Figure 1.

The system X acts as a data acquisition unit for the collection of data and making it fit for analysis. The information is further fed to the databases based on different data model structures from where the information is extracted for visualisation. In some cases, separate software's or computational models are required to have a deeper analysis depending on the complexity of the asset. Further, the data visualisation may have separate views based on the user's profile and needs.

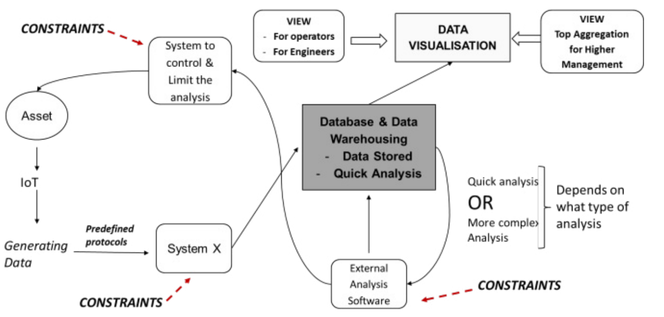

Fig. 1. Asset management digital flow

For DT development, along with potential constraints, it is important to understand requirements for system X, external analysis software and system limiting the analysis unit. System X is depending upon communication attributes such as IoT, smart sensor, and sensor fusion communication technologies. External systems for analysis are driven by the complexity of analysis. Machine learning and multi-level data analysis are promising. The external systems to limit analysis is the gateway to establish the feedback loop across the asset and its virtual representation. The knowledge for limiting the analysis should be driven by design parameters and in-service behaviour patterns of the asset.

3.3. Framework

The IM framework requirements are captured based on different views across the aircraft lifecycle. The view-based approach covers both the product and process constraints for the development of a digital twin. With continuous industrial engagement, requirements across different views are collected. Each business function has different view on data and information. The different views are: (a) IM View, (b) Engineering view, along which preliminary functional requirements for framework development identified, shown in Table 1:

Table 1. Requirements for framework development

Requirement	Description
Minimum information	Access to the minimum level of information for DT development such as data types, data views, etc.
Critical Requirements at physical layer	Identification and access to the requirements based on DT essential components such as Product Identification, Data Management, DT Model, IM, etc.
Different data views	Highlight different data views and defining the requirement for each view. This also includes definition of the context to support each view.
Dynamic requirements	Access to changes in requirements for DT development w.r.t. change in scale of application from the Requirement Engineering perspective.
Level of configuration information	Enable the access to the minimum level of configuration information required for a specific business case or case study.
Data mapping	Map the different type to data to DT ontology model classes, either based on standards or case driven.
Fidelity of the system	Access to minimum data set knowledge for its DT to ensure the fidelity of system.

Based on these requirements, the IM framework for DT is proposed. The overall framework is divided among the four layers: physical, data acquisition, model and data model layer, shown in Figure 2. The overall framework will enable the following:

a. Capture the high-level system and data requirements for the DT development for the physical product at a hierarchy of the physical product at the aircraft level. The requirements are semantically modelled.
b. The data acquisition layer focuses on the capturing of the data from different systems.
c. Model layer focuses on identifying the relationship between different models to be embedded in the DT and mapping the integration based on the data flows. The inclusion of the models is solely driven by the outcome/application of DT in the service phases of the product lifecycle.
d. The data model layer focuses on capturing the minimum data structure required for DT data model.

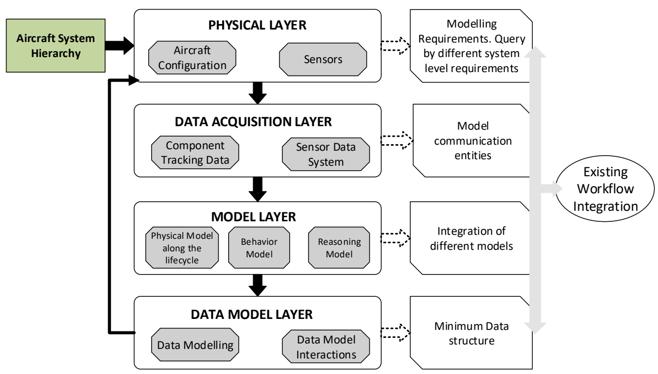

Fig. 2. DT IM Framework

Each time information is exchanged between different layers, a workflow is created. At an enterprise level, multiple workflows exist within the business process. The integration of existing workflows becomes essential along with the IM activities around DT. The proposed framework requires multi-disciplinary approach to define requirements and manage information along the lifecycle. The dynamic nature of requirements at the physical layer is suggested to be captured semantically in the form of ontologies. Software Protégé is widely used to create and maintain ontologies [15]. Once the requirements are captured in physical layer, data acquisition highlights the data capturing and connectivity aspects to DT. Capturing data depends on the existing system and organisational best practices. The overall communication architecture needs to be flexible to accommodate different IoT based connectivity solutions within the scope of the framework.

Activities for the model layer can be covered with using current Model Based System Engineering (MBSE) methods. Platforms such as 3D experience [16] are revolutionising the current way of modelling the products and information around it. Such platforms provide competitive advantages in terms of integrated simulations and visualisations. Data model layer focusses on extracting minimum structure for DT data model. The data modelling and further storage can be done in either graph-based platforms or relational databases based on the current practices the systems are maintained. The dynamic behaviour of the data model structure directly affects the change in scale and requirements in the physical layer. Therefore, use of ontologies is recommended to derive the minimum data structure. The five-step methodology to cover this aspect is discussed [17].

3.4. DT IM Phases

The IM for an aircraft is highly complex and demanding. It involves managing multiple streams of data capturing, processing and storage, development and maintenance of software, tools, licences, etc. to ensure the availability of information among various business functions. IM for DT for aircraft manufacturing industry requires a holistic approach to information. The difference between data, information and knowledge is well explained [18]. DT has the capability to support the transformation from data to knowledge. DT is the integration of models along the product lifecycle using data in real-time to provide valuable information about asset behaviour and such information retains as knowledge for long-term system sustainment and usage. Therefore, the IM framework requires a more holistic approach around data, information and knowledge. As the building blocks of the proposed framework, we have divided the IM throughout DT in aircraft manufacturing industry in four different phases, as shown in Figure 3.

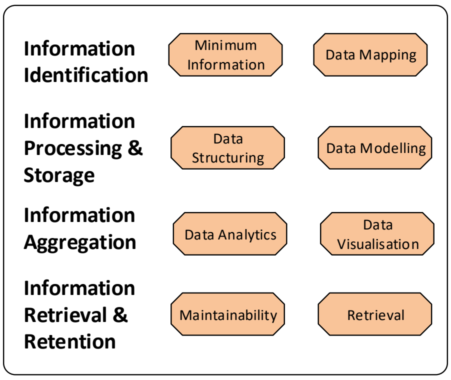

Fig. 3. DT IM phases

3.4.1. Information identification

The phase of Information identification refers to identifying the essential requirements for DT development and sustainment. Information identification includes elements such as minimum information and data mapping. Minimum information model denotes the minimum level of information necessary for DT development. Minimum information is important not only for the value chain but also crucial to solve big data complexities. Data mapping is an important activity of this phase. In general, data mapping is the process of creating data element mappings and establishing relationships between different data sources [19]. For the development of DT, mapping data and managing along the DT lifecycle becomes crucial. Data mapping for DT is not only about the integration of real-time data to existing simulation models, data mapping needs to be dynamic as DT becomes more scalable and complex.

3.4.2. Information process and storage

Along with information identification, understanding the information processing and how it is stored/organised is also the part of the IM landscape. The core activities of this phase include data structuring and data modelling. Aerospace manufacturing industries evolve in a complex environment of information keeping and data organisation. The tools and models built in engineering may defer from being used in manufacturing and testing. Therefore, data structuring and modelling become important for DT. Better data structures lead to less complexity and adaptable to changes easily.

3.4.3. Information aggregation

In aerospace manufacturing domain, the power of DT can be harnessed from the design to the in-service phase of the aircraft. DT provides the current state of the product or system but also provide additional insights. Extraction and representation of useful information for DT is the purpose of the third IM phase. The core activities to support this phase includes data analytics and data visualisation. Data analytics technique is widely used in industry to conclude the useful information by examining related data sets. Data analytics enables that how data is analysed to get desirable results. Data visualisation covers how information is aggregated and visualised as per different users per different views.

3.4.4. Information retrieval and retention

The last phase of DT IM is about information retrieval and retention. This phase involves activities of information maintainability and retrieval along the DT lifecycle. Maintainability of information is an important aspect for DT use in the long-term. As DT solutions may be implemented, the changes in requirements along project lifecycle are common. Therefore, for the long run, it is important to maintain the information which is subjected to long-term application and retention. Information retention is the action of obtaining information system resources that are relevant to an information need from a collection of information resources. Information retrieval process and data organisation go hand in hand. Therefore, extracting the right information in response to the specific query at appropriate query response time is important for highly safety-critical systems in an aircraft.

3.5. DT Information Flow

As DT is heavily driven by information across the asset/system, IM become one of the key aspects. With an information point of view, we defined the multi-layer information flow across DT. As shown in Figure 4, the information flow establishes among each layer contains a different set of information that can complete the information cycle along with the DT. The information flow steps are defined as follows:

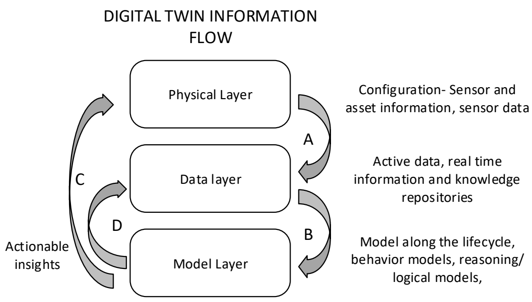

Fig. 4. DT Information Flow

Physical layer to data layer: The physical layer denotes the physical entities of DT such as asset. The physical layer is restricted to configuration information related to asset and raw sensor data. Configuration information is used as a signature throughout DT lifecycle whereas raw sensor data is further filtered and manipulated in the data layer. The configuration information provides traceability [20] and helps in information organisation across DT.

Data layer to model layer: The data layer denotes the data fits for analysis and knowledge repositories. The knowledge repositories hold business rules, logics and historical information about the asset. This manipulated sensor data is not only fit for models to run simulation but also increases understandability and accuracy. The knowledge repository supply historical data and business rules to model layer to provide valuable insights about the asset.

Model layer to physical layer: The model layer holds model along the lifecycle, behaviour model and logical models for reasoning. These models use information from the data layer to provide actionable insights by predicting failures and detecting the current state. These insights are implemented in the physical layer as a maintenance operation and service strategy.

Model layer to data layer: The information generated in the model layer is stored back to the knowledge repositories in the data layer. Such information contains analysis reports and recommendations that need to be used for the next DT analysis cycle. Such information serves back the model layer as historical data.

4. Case Study

A damage tolerance in an aircraft wing is formalised as a case study to understand the potential application and benefits of the framework [21]. Fatigue crack growth and propagation is a classic problem encountered within aircraft structures. On applying the proposed framework will enable engineers and IM specialists to work closely for developing DT and maintaining it further, shown in Figure 5.

The physical layer is identifying the existing requirements of the system which are captured in the form of requirement model. Ontology is one of the dynamic ways of semantically capturing and maintaining requirements as a form of knowledge [22]. The requirements need to be continuously updated with the actors. Further, the actual data capturing and processing are the function of data acquisition and model layer respectively. In the data acquisition, sensor data is collected for the number of fatigue cycles and strain measurement using a smart IoT based solution. The data acquisition unit is dedicated to filtering and pre-processing the data.

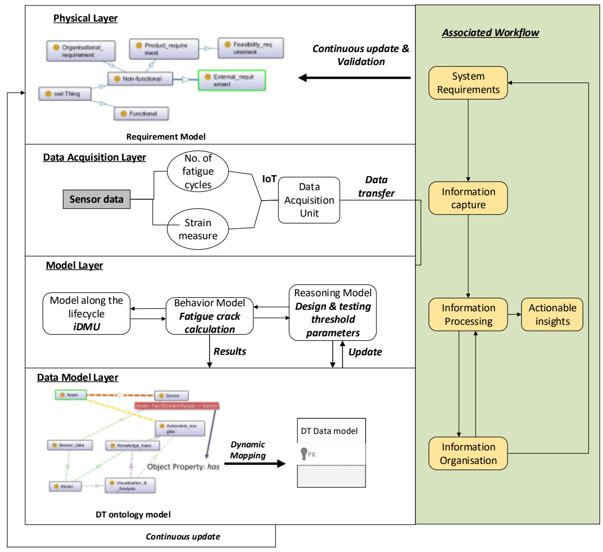

Fig. 5. DT IM for Aircraft Wing Structures

The model layer is where data is transformed into valuable information and actionable insights. Model along the lifecycle, DMU (Digital Mock-up) is widely known in the industry [23]. DMU consists of CAD, BOM (Bill of Material) and related configuration information. A behaviour model for the fatigue crack calculation developed during design and testing phase of the wing structure is calculated. Reasoning model covers knowledge related to design and testing threshold parameters. Such parameters include additional knowledge from the service and maintenance on ground that would also enable DT to match existing crack growth to the initial design and testing specifications. All these models need to be integrated and continuously updated along the DT lifecycle. Data model layer is where data is further structured and stored along DT lifecycle. The five-step methodology [17] to identify minimum data structure and model data for DT. DT ontology model acts as a guide to divide the data from acquisition layer and results from model layer among the different classes. Such division leads to an optimised data structure for DT data model. The data model structure will enable different actors to develop application specific DT interfaces and dashboards. Continuous updating data structures should be aligned with requirement model in the physical layer. The associated workflow defines the necessary tasks while applying framework across the enterprise.

5. Conclusion & Future Directions

The aircraft manufacturing industry offers many DT application opportunities but require streamlined approaches. One of the important aspects is IM. The existing literature and research lacks such an IM framework approach for DT.

In this paper, challenges of big data, information sharing & organisation and scalability for DT are discussed in IM context. The existing ways of managing an industrial asset shows the different dependencies and constraints that DT may put on the overall system. The proposed IM framework is constructed based on four IM phases. Further, the proposed information flow for DT enables ones to understand the flow of information among different layers. Across all the three layers: physical, data and model layer, information flow establishes continuous exchange of information and its type along the DT lifecycle. With the understanding of IM phases and information flow, a multi-layered framework is proposed based on common requirements from IM & engineering views. Further, a case study for aircraft structure damage tolerance has been formalised for the framework. Framework helps in understanding the different phases of IM from identification to retrieval and retention. The framework will allow industries to explore the dependencies of system requirements on IM for DT. The four-layered framework covers understanding minimum information to develop DT, data capturing and processing, and further modelling data for DT, thus reducing cycle time in DT development. The continuous interacting and updating four layers will resolve challenges of big data and information organisation along DT lifecycle. The framework provides an adequate balance between IM and engineering domains which is primarily missing in existing literature.

DT development and managing information become more complex as the complexity of the system or product increases. The proposed framework has the capability of serving multiple applications along the aircraft lifecycle. The framework targets mainly to support DT development activities in manufacturing and in-service phases of the aircraft lifecycle. It is also targeting to support some design feedback loop DT development activities with some caliberations. As future work, testing robustness of the framework with multiple detailed case studies can provide extended benefits in the area of research and industrial domain.

Acknowledgements

The authors would like to thank the Engineering and Physical Sciences Research Council (EPSRC) and AIRBUS for funding this research project. The project is funded via ICASE studentship (2017) which is part of the EPSRC National Productivity Investment Fund.

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