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Conceptual framework of a digital twin to evaluate the degradation status of complex engineering systems

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Abstract

Degradation of engineering structures and systems often comes in the form of wear, corrosion, and fracture. These factors progressively bring about performance decay, until the system fails to function satisfactorily. Complex engineering systems (CES) need regular maintenance throughout their operation, along with continuous checks on the health status of components and equipment, within regulatory frameworks. A digital twin paradigm is able to continuously monitor CES, to use this data to update a virtual model of the CES and thus make real-time predictions about future functionality. The purpose of this paper is to introduce a conceptual framework of a digital twin to be applied within the degradation assessment process of a CES. The digital twin framework will aim to gather digital data through a network to plan through-life requirements of the system. Data-driven approaches can be used to predict how degradation evolves over time. The proposed framework will help the decision-making process to better handle maintenance operations and achieve targets such as asset availability and minimised cost.

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Keywords: Product digital twin; materials degradation; conceptual framework; models integration; distributed systems.

1. Introduction

The increasing employment of modelling and simulation methods for complex engineering systems (CES), together with the growing amount of available data across the product lifecycle, lead to the use of the digital twin paradigm that can combine these two trends. The digital twin concept emerged from the aerospace companies, arising from the need to monitor and control the distant asset through a virtual replica of it. This lead to growing complexity and high-performance computing (HPC) necessary to develop a digital twin [1]. Advances in digital representation and data collection have been achieved in the last few decades and as a consequence, an effort towards implementation in the industrial sector is increasing.

Digital twins well attuned to the data architecture they face may be very well suited as tools for monitoring of the degradation on CES. Degradation of engineering structures and systems often comes in the form of wear, corrosion, and fracture [2]. Typically these factors progressively bring about performance decay, until the system fails to function satisfactorily. In much of the literature on digital twins, models can be found which tend to focus on specific problems. Consideration of degradation of CES, in contrast, requires models of much wider scope to be fit for purpose as digital twins [3,4]. There is an emerging literature on such digital twin

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models, which may be thought of as integrated structural digital twins, which aim to offer potential as digital counterparts of physical CES. The opportunities, risk and requirements of such an integrated approach are not fully understood yet [5]. Moreover, the integration of multiple modelling modalities into such digital twins entails an increasing complexity in the storage of data and communication as described in [3,6]. The increasing amount of available information and the ability to swap this data between models drives the need for a clear and structured architecture with a proper ontology, as highlighted in [7] and with a laboratory example in [8].

With the start point of an existing materials degradation assessment model [9], the aim of this work is to integrate that model into a digital twin framework, which itself is capable of further integration into a wider digital twin architecture. A long-term vision might be to develop a digital twin for degradation assessment and the ability to predict the remaining useful life (RUL) of the asset of interest.

2. Literature review

The digital twin concept, originally described as a digital replica to a physical asset, was introduced by Michael Grieves at the University of Michigan [10]. Figure 1 shows an early diagrammatic representation of the digital twin model composed of 3 parts, the physical space, the virtual space, and the data/information exchange between the two. Since then, many definitions of digital twin concept have evolved, mostly depending on the application that the digital twin has been applied to. However, the use of digital twins throughout the whole-life of CES, from design to in service to the end of life, is still in its infancy. Initially, the digital twin was intended to just mirror the life of air vehicles, then in 2015, the concept was extended into other fields including CES [11], in part also due to the fast development of the internet of things (IoT) across many industries. For example, in 2017 Negri et al [7] consider a digital twin in the context of manufacturing systems.

For the sake of clarity, a definition of the digital twin is given as combination of existing other definitions [4,12]. It is defined as a high-fidelity integrated model that can coordinate discipline-specific models (such as architecture, mechanical, electrical, software, verification, degradation assessment, etc.) across the system lifecycle of interest, merging models from multiple existing tools, to monitor the real-time conditions and predict future circumstances.

Materials degradation has been of interest for many years and is well described in the book by Batchelor et al [2]. A representation of a typical degradation of a material over time is shown in Figure 2 where terms like failure and loss of

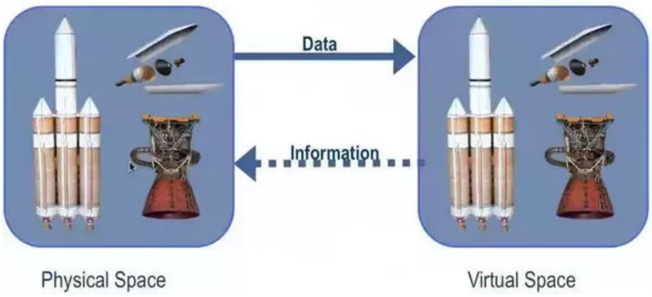

Figure 1 - First concept of digital twin (by M. Grieves - 2010)

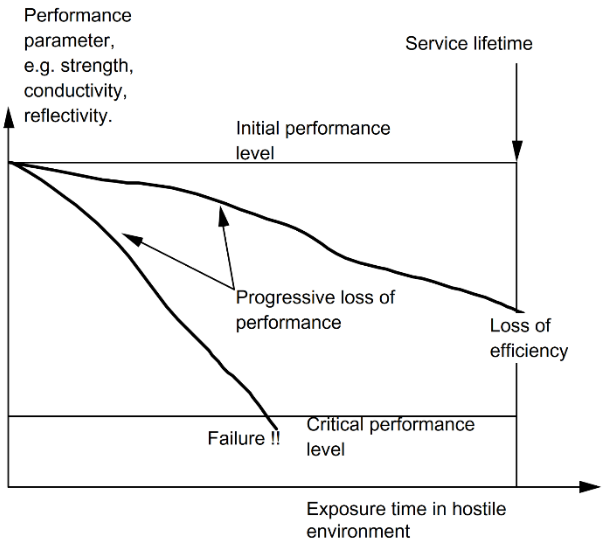

Figure 2 - Graphical definition of materials degradation as loss of performance of an engineering system. (Batchelor et al.)

efficacy have been clearly illustrated. In fact, failure occurs when the performance declines below the critical level, whereas loss of efficiency occurs if performance declines but remains above the critical level during the operation life. The length between the initial performance level and the failure point is defined as the RUL.

Many natural phenomenon cause materials degradation, such as heat, light, short-wavelength electromagnetic radiation, radioactive emissions, chemicals, mechanical stress and interaction with bacteria, fungi or other life forms. As can be seen Figure 3 there are three basic categories for materials degradation: physical, chemical, and biological. Physical origin refers to the effect of force, heat, and radiation. Chemical origin relates to destructive reactions between the material and chemicals that contact it. Biological origin includes all interactions between life forms and engineering materials.

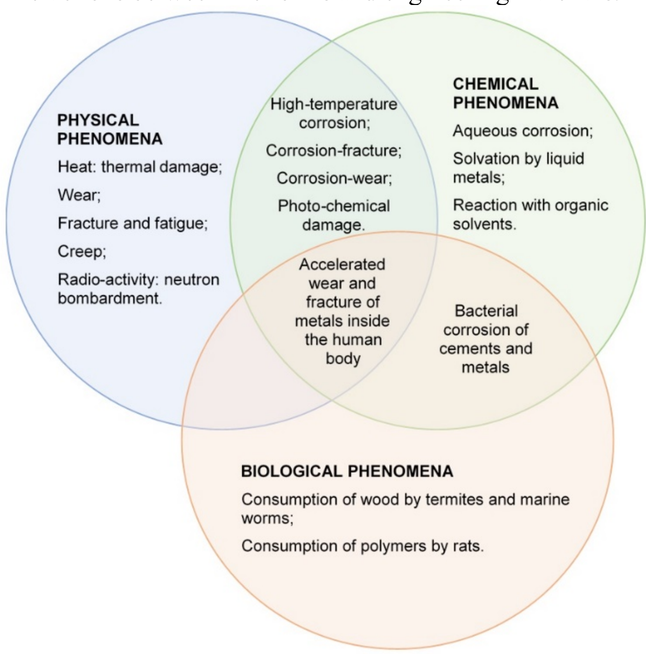

Figure 3 - Classification of materials degradation (Extracted from Batchelor et al.)

Digital twins for degradation assessment have been considered in the literature. In particular, the digital twin has been proposed to monitor anomalies, fatigue, crack propagation in the physical counterpart [1,12–17]; to monitor geometric and plastic deformation on the material of the physical counterpart [18]; and to model the reliability of the physical counterpart [19].

Figure 4 illustrates a spectrum of applications where the digital twin paradigm can be helpful if applied to each phase of the lifecycle [1]. Monitoring the condition of the asset during the operation phase, allows the digital twin to plan preventive maintenance more efficiently. However, the practicalities of doing it would be difficult and require time and HPC to model and manage different types of damage. Cerrone et al [16] used a finite element modelling (FEM) tool to more accurately predict cracking on a specific component. They also pointed out the importance of modelling and simulating the as-manufactured component, instead of the as-designed one, to better predict the crack propagation.

From the analysis of the scientific literature in digital twins for materials degradation assessment, what is missing today is a digital twin able to integrate different models, rather than focusing on just one aspect of the degradation of the materials (as reported in [12,16]). Furthermore, the application of a compound materials degradation assessment could bring a forward step in the digital twin paradigm to predict the RUL of the asset of interest. Models integration inside the digital twin architecture is getting increasing attention in the scientific literature. As mentioned by Vrabič et al [3] the integration of different models impacts positively in the whole product lifecycle. In fact, this integration approach helps to reduce costs and time-to-market; thanks to the simulation feature [20] which improves the simulation fidelity with real-time data, integrates maintenance information increasing availability and reliability [6], and integrates the learning module to optimise the overall operation. However, this is a highly complicated task and an integrated architecture allows the models, coming from several tools, to communicate with each other.

Aivaliotis et al [21] define a guide for creating a physical-based model to enable digital twin concept in predictive maintenance applications. The need, in this case, is to integrate such kind of approach in a more generic structured framework, able to evaluate the machine health status. An interesting digital twin case study of application within a framework is presented by Tao et al in [22].

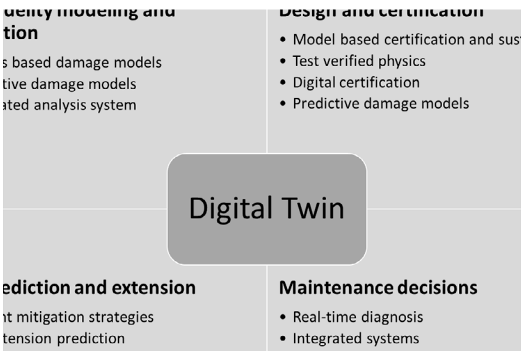

Figure 4 - Integration of technologies within a digital twin (Adapted from Glaessgen et al.)

An efficient approach to face this models integration issue is explained in the *Eclipse Ditto* project [23]. Considering the digital twin as a virtual, cloud-based, representation of the physical world, *Ditto* can be applied as a communication pattern that simplifies the communication between models. The architecture proposed allows the digital twin to be treated as a web app that asks and provides information to the model. A similar approach to the communication aspect has been considered for the conceptual model explained in the following section.

3. Conceptual framework of the digital twin

The main objective of the digital twin is to enhance the level of understanding of the asset of interest to be able to increase the availability and minimise costs throughout the whole lifecycle. In order to achieve this target, a conceptual framework has been proposed that allows efficient exchange of information across different models, which have been siloed in their own scope so far. The stream of data circulating underneath the digital world is called the digital thread, this keeps the real and virtual world synchronised. The transmission of the data starts in the design phase and lasts for the entire life of the asset of interest.

The digital twin has been conceptualised in the through-life engineering services (TES) environment. TES has been defined in PAS 280:2018 as the set of capabilities, techniques and behaviours that are applied to major assets over their entire lifecycle to achieve optimum value in use at entry into service and through-life. The conceptualisation of digital twins in the TES environment has been given by Erkoyuncu et al [5] where the study showed that digital twins offer significant opportunities to manage the defined development requirements and monitor them over the lifecycle, particularly in the 'in-service' phase. However, the adoption of this paradigm will require organisational and process changes across the industry to enable effective collaboration. The future challenges highlighted are, among others, the connectivity across different data sources, accurate real-life analytics, and increased measurement and data acquisition. The digital twin as defined in PAS 280:2018, is a full digital representation of a product, incorporating high fidelity virtual product models and digital records of the attributes that define a product or component throughout its entire product lifecycle.

Particular focus has been given for the capability of the digital twin to predict the RUL of the asset of interest through the materials degradation assessment.

3.1 Proposed conceptual architecture for digital twins

Figure 5 represents the conceptual framework of the digital twin. The set represented by the model together with the interface and the database forms the module box. The conceptual framework is composed of the *digital twin central unit* and the *modules*. A particular module is the visualisation module, which is used to represent the output of the digital twin in various forms explained later in the section; where the cloud indicates that one or more modules can lie on the cloud with possible advantages as summarised below.

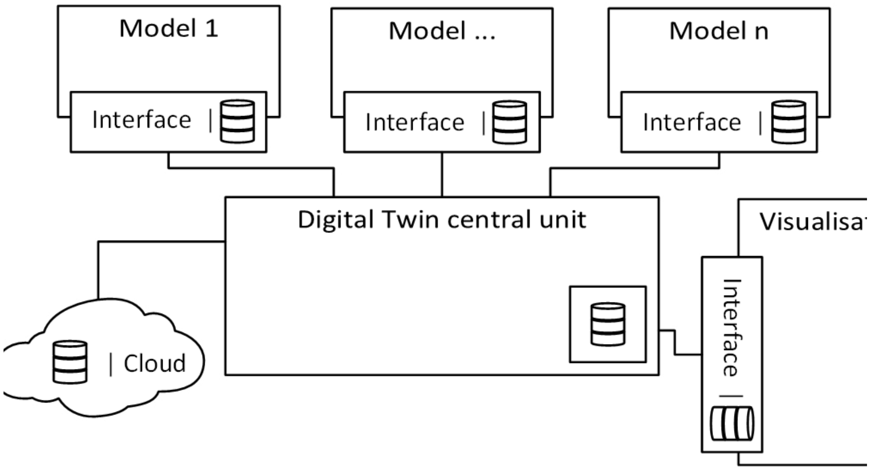

Figure 5 - Conceptual framework of the digital twin

Each model can be written in its own programming language or contained in its specific tool (commercial or open source). Therefore, an interface must be attached to each model with the function of translating the data from the language of the model to the common language inside the central unit of the digital twin. A similar function can be found on the web with the application programming interface (API). APIs, indeed, are currently used from the main data provider to share data with other websites, without allowing entry into the provider's website architecture. After querying what is needed, the data provider sends all the data through a JSON message. An application of the APIs in a digital twin has been also suggested as the potential future implementation by Bajaj et al [4].

The common language of the documents circulating inside the central unit is structured as a JSON message. Those JSON messages can then be used by all the tools and all the programming languages in a flexible way, extracting the data that are required by the potential querying module. Models can also lie in the cloud and be connected to other models belonging to other digital twins to increase the knowledge of the whole fleet. This could be the case of the learning model, which can then learn also from other digital twins within the network.

The conceptual framework is composed of 3 main layers: the data architecture, the modules and the interconnection across modules. Concerning the data architecture, as can be seen in Figure 5, each module and the central unit contain a database. This opens to a distributed intelligence within the system in which every module can manage its own data. The database in the central unit contains the data useful for the real-time operation representation, while each database in each module contains the historical data relative to the module itself. The data management system can be SQL or NoSQL, and the decision is dependent on the data structure of the modules. Both SQL and NoSQL systems can be perfectly integrated into the digital twin architecture, thanks to the compatibility with the JSON messages.

The central unit, thus, has the main feature of dispatching messages. It is capable of receiving requests from the modules and forwarding them to the interested modules, ensuring the correct flow of the data and messages. Moreover, the central unit is able to understand how many modules should be connected in the digital twin and checking their status, which can be ON, OFF, or DISCONNECTED. This ensures the high flexibility of the digital twin framework and allows the integration of a flexible number of models.

As in the internet field, in which lies a specific web semantic, the semantic of the digital world has received growing attention in the development of digital twins [8,24]. Establishing rules and a common nomenclature inside the twin will ensure the correct flow of messages and the capability to operate in a different context with a flexible number of models. For the above reasons, creating a strong and structured framework that distributes the data across the system is fundamental. The second step is to evaluate the models that best suit the analysis in the digital twin and, finally, integrates that selected models into the digital twin framework ensuring an efficient and fast communication across the modules.

As mentioned before, the digital twin framework relies on an integrated model approach, models that have been treated as silos so far. For instance, in the *CAD model,* all the components of the asset are created or imported in .step format, in this way they could be exported in any CAD software for further processing and analysis. The CAD model contains the physical attributes of the asset, such as the dimensions, the mass, the inertia, and the centre of gravity; the *environment model* gives information about the surroundings of the asset. This information is important for the digital twin since the latter is a high-fidelity and unique representation of the physical system. Often the environmental data are the main difference between two assets; in the *learning model*, it is possible to enable the simulation of the what-if scenarios where *experience-based models* can combine inputs and predict the output based on the training data I provided before. Machine learning (ML) algorithms take data from different models to learn and predict possible circumstances. This model can also be placed inside the cloud where ML algorithms from other digital twins can share data to optimise the whole fleet and assist the decision-making process; the *degradation assessment model* uses geometry data from the CAD model and real-time status from sensors or 3D scanners, to generate the output information that will predict the RUL of each component. In order to better predict the RUL, as discussed by Cerrone et al [16], the geometry data should reflect the as-manufactured geometry rather than the as-designed one.

One of the key aspects of the digital twin is to provide the outcome, in other words, the evidence-based results to support the decision-making process. These results can be displayed in the form of a web app, virtual reality, augmented reality, and of course a combination of them. The aim here is to provide all the back-end data, and the ability to feed any visualisation application needed by the end user.

The reason why the authors have chosen an integrated architecture is that combining models, considered as working stand-alone so far, can enhance the knowledge about the asset and improve the fidelity of the data used to predict the RUL. In this way, this could be used as an open framework that can integrate different models and let them communicate each other and also as a meeting point for the data provided from the growing used IIoT devices. Moreover, data-driven approaches, such as ML, used in a fleet context digital twin, rather than a single asset, can help in the long term production planning to reduce unpredicted downtime thanks to a data log history contained in the fleet digital twin.

The connection across modules can be either physical or virtual. To allow the modules to communicate effectively platforms such as machine-type communications (MTC), also known as machine-to-machine (M2M) communications are being increasingly used in IIoT applications. Based on the open framework OSI* (open systems interconnection) that can be adapted and customised depending on the network architecture designed for the digital twin. However, to ensure a reliable and efficient interaction across models, particular attention is needed in the selection of the communication protocol. The solution could be found in other fields, for instance, the protocols currently used for the IIoT and designing the network architecture following standardised industrial architectures developed using the OPC UA (open platform communication unified architecture) is a good example [25]. A discussion about a reliable and efficient communication pattern useful in our conceptual architecture can be found in D'Amico et al [26], where, in the field of cyber-physical production systems (CPPS), the asynchronous messaging library ZeroMQ [27] has been preferred to MQTT [28], for the higher reliability and flexibility in distributed applications.

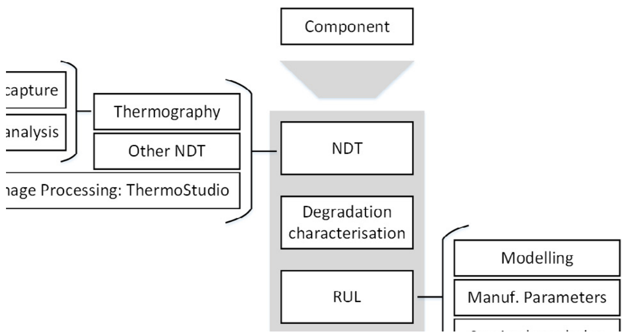

Figure 6 – Component level materials degradation assessment model for NDT, related to the thermography setup (from Addepalli et al.)

3.2 Integration of the materials degradation assessment model in the digital twin framework

The integration of models in the digital twin occurs, thanks to the capability of the framework to host a flexible amount of models. A list of modules is loaded into the central unit, it is able, then, to check the status of each module that should be connected (ON, OFF, or DISCONNECTED). Once checked the status of the module, the latter, if connected, has the capability to send and receive messages to and from each module within the digital twin.

The materials degradation assessment model (shown in Figure 6) analysed in this subsection has been proposed by Addepalli et al [9] and considers an automated thermographic inspection as a non-destructive test (NDT). The model can be explained as follows: when a part comes for service, the maintenance system performs the automated inspection using pulsed thermography where the entire process of part collection through to inspection and post-processing of data was fully automated. With the use of signal and image processing

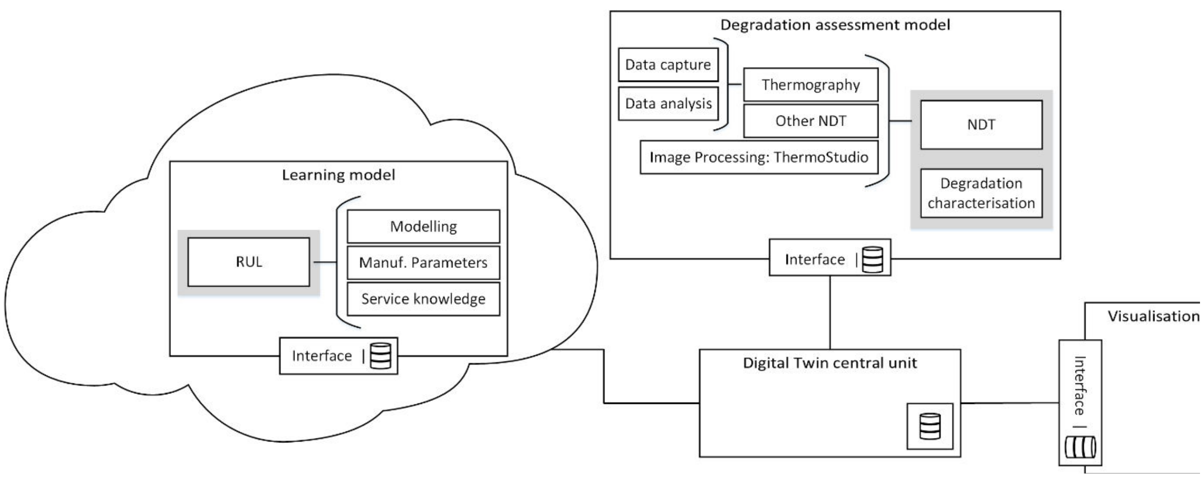

Figure 7 - Integration of the materials degradation assessment models in the digital twin framework

* ISO/IEC 7498-1

algorithms, thresholds were set up to identify critical areas showing degradation beyond acceptable levels thereby reducing any operator burden to sift through the dataset. The degradation model for this feedback based maintenance is dependent on the data from the inspection system, existing knowledge on the history of the inspected part, and on the remaining useful life algorithms that help predict and establish a time to failure with a confidence band.

The materials degradation assessment model has input, from the top left and bottom right of Figure 6, and output, which in this case, after the characterisation of the degradation that presents the RUL (predicted). It can be integrated inside the digital twin framework proposed, dividing the workflow in two since, after the characterization, the prediction of the RUL can occur in the learning model placed on the cloud. The model can take the information relative to the geometry and material from the CAD model, perform the automated thermography inspection as NDT, elaborate the data inside the model, and process the final image with a tool called ThermoStudio. The results are analysed in the degradation characterization block that can then transfer the data inside the interface, in which are translated in JSON message ready to be sent to the learning module for the prediction of the RUL. Before sending the JSON message the record containing the pieces of information about materials degradation are stored in the database of the degradation assessment module. The payload with the degradation assessment data can now be sent to the learning module through the central unit. The RUL box, placed inside the learning module, can now predict the RUL thanks to the information collected from the degradation assessment module and share the prediction with all the modules connected to the digital twin framework including, of course, the visualization module that can let the end user see the prediction. The advantage of having the learning model in the cloud is, as mentioned in the previous subsection, that the prediction elaborated for the asset of interest is now available to enhance the knowledge of the whole fleet. A graphic interpretation of the integration is illustrated in Figure 7.

4. Conclusions and future challenges

The power of the proposed framework, which is also what is currently missing in research, is the integrated architecture across models. The central unit works as conveyor, transmitting the right message to the right model.

The paper contains an extensive literature review that considers a large number of definitions depending on the application of the digital twin. It also contains some insight from the materials degradation side, which can be included in the digital twin architecture as a plus compared to what has been considered so far. The main contribution is given by the interface that allows the model integration, which aims to integrate most of the existing models, today treated as silos, and to improve learning techniques that can add value to the results and performance of the digital twin. The interface, indeed, translates information to the language of the digital twin central unit, which will be the common language of the digital twin architecture.

Thanks to this complete architecture, the digital twin can also act as hardware-in-the-loop (HIL). In the case of an overhaul, indeed, the maintenance can be performed virtually, before actually performing it physically. The model of the component can be tested inside the digital twin, testing if the RUL is compatible with the rest of the system. Another example of an application of this framework is in the case of moving the asset in another environment, the digital twin can test the overall behaviour and the RUL of the components contextualized in the new virtual environment before actually moving it.

In a pan-industry survey conducted by Erkoyuncu et al [5], it emerged that: i) much of the digital twin technology is already available in the market, but this has not been integrated yet to create a full digital twin; ii) the in-service phase can benefit more for the digital twin and; iii) there are many cultural challenges to the introduction of the digital twin. For these reasons a complete architecture of digital twin must allow the integration across different tools, which today speak different languages, and it must be easy to implement and in particular easy to use.

The proposed conceptual framework of digital twin focuses on the evaluation of the RUL of a component or an asset with the through-life engineering perspective.

The conceptual framework proposed is open and general and hence could be applied in many fields, nonetheless, this could be the starting point to consider the more in-depth analysis of the digital twin for a use case. Moreover, this architecture shows the digital twin should be a share point where hardware and software companies meet each other exchanging useful information enhancing the overall knowledge of the asset of interest. For this reason, it is really important to create the creation of a complete and strong ontology, which should regulate the roles and the hierarchy inside the architecture, and that ontology must be adopted by each interface of the digital twin.

It has been shown as the digital twin could assist the decision-making process both in operation and in service mode, thanks also to the HIL feature. Additionally, thanks to the data stored during the lifetime of the system and to the learning algorithms, the digital twin could be used to assist the design phase in the creation of future improved assets. Furthermore, an important contribution can come from a compound degradation assessment, which will consider the combination of different models to better evaluate the health status of the asset.

Future work will focus on the application of this architecture to a real use case, benchmarking the different communication protocols and libraries to speed up and ensure the correct circulation of information across models. Compare the results of an integrated approach with the ones obtained with using all the models and simulators in a stand-alone way. The final objective is to reduce the efforts needed for the model's integration as well as the integration of different commercial and open tools.

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References

[1]. Glaessgen E., Stargel D. The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles. 53rd Structures, Structural Dynamics, and Materials Conference. Special Session on the Digital Twin. 2012. pp. 1–14. Available at: DOI:10.2514/6.2012-1818

[2]. Batchelor AW., Lam LN., Chandrasekaran M. Materials Degradation and Its Control by Surface Engineering. 2nd edn. Imperial College Press; 2002. 412 p.

[3]. Vrabič R., Erkoyuncu JA., Butala P., Roy R. Digital twins: Understanding the added value of integrated models for through-life engineering services. Procedia Manufacturing. Elsevier B.V.; 2018. pp. 139–146. Available at: DOI:10.1016/j.promfg.2018.10.167

[4]. Bajaj M., Cole B., Zwemer D. Architecture To Geometry - Integrating System Models With Mechanical Design. 2016; : 1–19. Available at: DOI:10.2514/6.2016-5470

[5]. Erkoyuncu JA., Birkin G., Carvalho do lago RL., Williamson A., Williams H., Roy R. Conceptualisation of Digital Twins in the Through-life Engineering Services Environment. : 3–25.

[6]. Tao F., Sui F., Liu A., Qi Q., Zhang M., Song B., et al. Digital twin-driven product design framework. International Journal of Production Research. Taylor & Francis; 2018; 7543: 1–19. Available at: DOI:10.1080/00207543.2018.1443229

[7]. Negri E., Fumagalli L., Macchi M. A Review of the Roles of Digital Twin in CPS-based Production Systems. Procedia Manufacturing. The Author(s); 2017. pp. 939–948. Available at: DOI:10.1016/j.promfg.2017.07.198

[8]. Negri E., Fumagalli L., Cimino C., Macchi M. FMU-supported simulation for CPS Digital Twin. Procedia Manufacturing. Elsevier B.V.; 2019. pp. 201–206. Available at: DOI:10.1016/j.promfg.2018.12.033

[9]. Addepalli S., Roy R., Axinte D., Mehnen J. 'In-situ' Inspection Technologies: Trends in Degradation Assessment and Associated Technologies. Procedia CIRP. 2017; 59(TESConf 2016): 35–40. Available at: DOI:10.1016/j.procir.2016.10.003

[10]. Grieves M. Digital Twin : Manufacturing Excellence through Virtual Factory Replication. 2015; (March).

[11]. Ríos J., Hernández JC., Oliva M., Mas F. Product avatar as digital counterpart of a physical individual product: Literature review and implications in an aircraft. Advances in Transdisciplinary Engineering. 2015; 2: 657–666. Available at: DOI:10.3233/978-1-61499-544-9-657

[12]. Bazilevs Y., Deng X., Korobenko A., Lanza di Scalea F., Todd MD., Taylor SG. Isogeometric Fatigue Damage Prediction in Large-Scale Composite Structures Driven by Dynamic Sensor Data. Journal of Applied Mechanics. 2015; 82(9): 091008. Available at: DOI:10.1115/1.4030795

[13]. Tuegel E. The Airframe Digital Twin: Some Challenges to Realization. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference. 2012. pp. 1–8. Available at: DOI:10.2514/6.2012-1812

[14]. Reifsnider K., Majumdar P. Multiphysics Stimulated Simulation Digital Twin Methods for Fleet Management. Structures, Structural Dynamics, and Materials and Co-located Conferences. 2013. pp. 1–11. Available at: DOI:10.2514/6.2013-1578

[15]. Schroeder GN., Steinmetz C., Pereira CE., Espindola DB. Digital Twin Data Modeling with AutomationML and a Communication Methodology for Data Exchange. IFAC-PapersOnLine. Elsevier B.V.; 2016. pp. 12–17. Available at: DOI:10.1016/j.ifacol.2016.11.115

[16]. Cerrone A., Hochhalter J., Heber G., Ingraffea A. On the effects of modeling as-manufactured geometry: toward digital twin. Hindawi.Com. 2014; 2014: 10. Available at: DOI:http://dx.doi.org/10.1155/2014/439278

[17]. Fourgeau E., Gomez E., Adli H., Fernandes C., Hagege M. System engineering workbench for multi-views systems methodology with 3DExperience platform. The aircraft Radar use case. Advances in Intelligent Systems and Computing. 2016; 426: 269–270. Available at: DOI:10.1007/978-3-319-29643-2_21

[18]. Yang J., Zhang W., Liu Y. Subcycle Fatigue Crack Growth Mechanism Investigation for Aluminum Alloys and Steel. Structures, Structural Dynamics, and Materials and Co-located Conferences. 2013. pp. 1–7. Available at: DOI:10.2514/6.2013-1499

[19]. Gockel B., Tudor A., Brandyberry M., Penmetsa R., Tuegel E. Challenges with Structural Life Forecasting Using Realistic Mission Profiles. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference. 2012. pp. 1–11. Available at: DOI:10.2514/6.2012-1813

[20]. Boschert S., Rosen R. Digital Twin - The simulation aspect. Mechatronic Futures: Challenges and Solutions for Mechatronic Systems and Their Designers. 2016. pp. 1–259. Available at: DOI:10.1007/978-3-319-32156-1

[21]. Aivaliotis P., Georgoulias K., Arkouli Z., Makris S. Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance. Procedia CIRP. Elsevier B.V.; 2019; 81: 417–422. Available at: DOI:10.1016/j.procir.2019.03.072

[22]. Tao F., Zhang M., Liu Y., Nee AYC. Digital twin driven prognostics and health management for complex equipment. CIRP Annals. CIRP; 2018; 67(1): 169–172. Available at: DOI:10.1016/j.cirp.2018.04.055

[23]. Eclipse Foundation. Eclipse Ditto. 2018. Available at: https://www.eclipse.org/ditto/intro-overview.html (Accessed: 10 May 2019)

[24]. David J., Lobov A., Lanz M. Attaining Learning Objectives by Ontological Reasoning using Digital Twins. Procedia Manufacturing. Elsevier B.V.; 2019; 31: 349–355. Available at: DOI:10.1016/j.promfg.2019.03.055

[25]. OPC foundation. OPC UA. 2008. Available at: https://opcfoundation.org/about/opc-technologies/opc-ua/

[26]. D'Amico RD., Egger G., Giusti A., Rauch E., Riedl M., Matt DT. Communication Concept of DeConSim: A Decentralized Control Simulator for Production Systems. Procedia Manufacturing. 2018. pp. 100–106. Available at: DOI:10.1016/j.promfg.2018.06.015

[27]. ZeroMQ. Available at: http://zeromq.org/

[28]. MQTT. Available at: http://mqtt.org/