Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 51-11 (2018) 790–795

Exploring the role of Digital Twin for Asset Lifecycle Management

Marco Macchi*, Irene Roda*, Elisa Negri*, Luca Fumagalli*

**Department of Management, Economics and Industrial Engineering, Politecnico di Milano, P.za Leonardo da Vinci 32, 20133 Milano, Italy - Contact author's email: irene.roda@polimi.it*

Abstract: This work is an explorative study to reflect on the role of digital twins to support decision-making in asset lifecycle management. The study remarks the current convergence of needs for decision support from Asset Management and of potentials for decision support offered by Digital Twin modeling. The importance of digital twins is evident through state of the art as well as practical use case analysis.

Keywords: Asset management, Lifecycle management, Digital twin, Decision support.

1. INTRODUCTION

Nowadays, Asset Management (AM) has gained considerable momentum and interest in both academia and industry as a business process and as a discipline (El-Akruti et al., 2013). The ISO 5500X body of standards (ISO 55000, 2014) contributed reinforcing it. The established consensus is that AM can contribute to ensure proper management of the assets along the lifecycle (Schuman and Brent 2005; El-Akruti et al., 2013): the assets are brought at the center of the management process to create value along their lifecycle. Other processes, as maintenance management, contribute to AM, as they are seen as key activities part of the larger AM process (Hastings 2010; CSN EN 16646 2014; Amadi-Echendu and Brown 2010).

In AM, the asset-related decision-making process is a key matter (El-Akruti et al., 2013; Komonen et al., 2006): it requires proper tools for supporting the decision-making, and should be built based on principles that address the holistic vision associated to AM (Schuman and Brent 2005). A challenge to this end is enabling an informed decision-making, which requires a proper data/information management (Ouertani, Parlikad, and McFarlane 2008).

Information has always been a relevant issue well discussed within the AM body of knowledge (Ouertani, Parlikad, and McFarlane 2008; Borek et al. 2014; Kans and Ingwald 2008; Koronios, Lin, and Gao 2006). Today, the interest in debating information relevant for AM has been renewed as the recent breath of technological advancements is having a profound impact. Sensor-related technologies are enabling an extended data gathering, while advanced controls are promising the "zero/unplanned downtime" of assets, with a cost-effective management. These opportunities are worth of a study that looks at potentials for AM arising from digitization.

Digitization is related to the Internet of Things (IoT) concept and the convergent development of many other technologies discussed in the Fourth Industrial Revolution (aka Industry 4.0). As a founding concept, IoT sees the all devices, with embedded sensors, electronics and capabilities to connect to others, as "things". Such things allow to collect and exchange data through internet (Ashton 2009; Sarma, Brock, and Ashton 2000) and, in general, through networks of devices, named as smart objects (Atzori, Iera, and Morabito 2010). Big Data analytics, that access the data and promise to provide fast decision-making with the use of smart analytics tools (Davis et al. 2012; Lee, Kao, and Yang 2014), complement the IoT with further features useful for decision-making support. Advanced simulation is also discussed amongst the tools relevant for prediction of the stochastic processes that occur in the physical world (Negri, Fumagalli, and Macchi 2017).

In such a technology landscape, an important concept is often remarked: the Digital Twin (DT), meant as a system's digital counterpart along its lifecycle. The DT can be considered as a virtual entity, relying on the sensed and transmitted data of the IoT infrastructure as well as on the capability to elaborate data by means of Big Data technologies, with the purpose to allow optimizations and decision-making. In this scope, the DT is often overlapped with advanced simulation. Overall, the DT, as a virtual entity, can regard everything of the physical world, thus physical assets can also be directly taken as a target scope of DT modeling.

Some questions arise: what does really mean having a DT for a physical asset? What is the role of DTs in AM? Motivated by these questions, the intended purpose of this paper is to provide an exploration to discuss the role of DTs in AM, in particular in the asset-related decision-making process. Thus, this is a conceptual paper aiming at putting the basis for research to contribute to a wider understanding of the benefits of applying DTs in asset lifecycle management. Thanks to the knowledge gathered by the authors in the scope of different projects where they experienced the concept of DT in its use, a focus is adopted enabling to link the new technologies to their applications in industrial settings where asset-related decision-making is required. This field experience, developed and presented through five explorative application use cases, is complemented by a state of the art analysis providing the foundation of the study.

Section 2 synthesizes the state of the art on AM and its needs in terms of asset-related decision-making, and on DT concept and its potentials for decision support. Section 3 clears out the rationale behind the explorative study on DTs in AM. Section 4 provides a collection of experiences in different industrial projects, to analyze the use of the DT modeling concept. Conclusions in section 5 aims to stimulate future researches.

10.1016/j.ifacol.2018.08.415

2. STATE OF THE ART

2.1 Asset Management and the decision support needs

The main principles that are the foundations for proper asset-related decision-making within an AM system are the following (Roda and Macchi 2016):

- life cycle orientation, leading to incorporate long-term objectives and performances to drive decision-making;
- system orientation, motivating the relevance of a holistic consideration of asset systems in their entirety, and not merely of the individual components;
- risk orientation, relating to the relevance to consider risk as assets normally suffer from uncertainties in achieving stated objectives, thus, there is a subsequent need for risk management approaches;
- asset-centric orientation, leading to focus on asset data and information of the assets, to make sound business decisions.

In accordance to these principles, every time an asset-related decision has to be made, the company should consider two main aspects (El-Akruti et al. 2013; Roda and Macchi 2016)

- the asset lifecycle, hence the effect of that decision on the long term over the asset life cycle;
- the asset hierarchical control level, hence ensuring that whether the decision is taken at strategic, tactical or operative level within the company, proper actions are taken to ensure that the other levels are also aligned.

Both principles and aspects of decisions are, as a whole, the reasons determining specific decision support needs. Some examples may be helpful to deduce such needs.

As a first example, it is considered the case of an investment in a new industrial plant as a decision. In this case, a strategic view is certainly required, i.e. a strategic control level, to align, at the beginning of the asset lifecycle, to the long-term objectives and performances needed to generate value from the asset. Nevertheless, this is not enough. A tactical and/or operational view, capable to lead to a clear sensitivity to what will actually be happening as effect of a strategic decision, is also needed. Using these specific views would then lead to an informed decision-making. Eventually, this would enable to properly base the decision on the AM principles, e.g. a risk orientation will mean having it through different asset control levels, i.e. considering the risk at strategic, tactical, operative level. As a second example, it is considered a decision at the end of life of an asset. It may have, as options, two outcomes: to continue with the same asset based on a strategy for its life cycle extension (e.g. a revamping, a retrofitting etc.), or to proceed with the asset decommissioning (and, eventually, with the purchase of a new asset). As with the first example, also this decision requires a strategic view, while not lacking other tactical/operational views, thus not missing, e.g., the risk orientation at different asset control levels.

A question now arises after the examples: what is it needed to support such decisions? There is the need, firstly, to integrate a variety of information types (e.g. asset condition due to past decisions, functional role of the asset within the system, etc. …), usually dispersed in many information sources. In terms of decision-making process, there is, then, the need, at least, to reduce the time wastes that may occur when collecting the required information. Moreover, there is a clear need to avoid some inconsistency in the decisions with regard to the AM principles (which may emerge due to a lack of information). Think, for example, that, as some information is missed, there is an omission concerning the risk orientation: it may lead to potentially having a cascade effect on other AM principles, e.g. lifecycle orientation, as the achievement of performances / long-term objectives may be partially achievable, or not achievable at all.

All these needs require proper data/information management. Nowadays, to the best knowledge of the authors, there is not such a full support, as desired: data/information management is not fully linked to the lifecycle management of the assets. As a final effect, informed decisions are partially achievable. Therefore, the future years will require to develop a better decision support. For practical reasons, it can be assumed that the development occurs in the scope of the asset information systems actually existent, while extending the relationships to the lifecycle management of the assets. The DT modelling can be considered as a relevant concept to this end. The next subsection discusses its potentials.

2.2 Digital twin modeling to support lifecycle management

From literature, the DT did not receive a unique definition, probably because it was not always linked to a specific sector: it was first proposed in the aerospace field, then it was used in robotics and only recently it has been adopted also in the manufacturing domain (Negri, Fumagalli, and Macchi 2017). Its first formal definition was provided by the NASA as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. It is ultra-realistic and may consider one or more important and interdependent vehicle systems" (Shafto et al. 2010).

Two necessary aspects emerge, as basis of the DT modeling paradigm: the Data Modelling and the Data Analytics. On one hand, it is important to define a proper model of data / information of the system to be virtually represented. This deals with standards for data / systems representation, while is also connected with the possibility to simulate the system. To properly structure data models, literature cites semantic data models, such as ontologies as good candidates. They are explicit, shared, formal representations of concepts understandable by software systems and usable to include intelligence for the integration and sharing of big amount of data, such as the generated data from sensors in a system (Garetti, Fumagalli, and Negri 2015; Negri et al. 2016; Gruber 1995; Borgo 2014; Heymans et al. 2008). On the other hand, it is impossible to have a consistent virtual representation of a real system without the use of real-time sensed data from the system itself. It is a cumbersome task, without a proper data analytics supporting this.

Relying on such prerequisites, the concept and functionalities of the DT can be then understood. Indeed, the contribution by (Negri, Fumagalli, and Macchi 2017) helps to frame them by proposing a thorough literature review on this topic.

The DT was originally created in the aerospace field as the stochastics-based mirror of the aircraft life that replicated, through simulations, the continuous time history of the vehicle, using historical data, sensor data, maintenance information and simulating also interactions with the external world. It was intended to deeply understand what the vehicle experienced and to predict breakdowns and needs (Wang et al. 2015; Bazilevs et al. 2015; Bajaj, Zwemer, and Cole 2016; Ríos et al. 2016). The translation of the DT concept for the robotics environment meant another objective for the DT, which was seen as the "tool" to optimize control algorithms of robots during the development phase (Schluse and Rossmann 2016). When adopted in manufacturing, the DT has taken a new objective: to simulate the complex behaviour of production systems, also including external factors, as human presence and technical constraints (Rosen et al. 2015; Gabor et al. 2016; Arisoy et al. 2017). Overall, a number of functionalities for the use DTs is reported in literature, amongst them:

1. improved maintenance decision making (damage / cracks prediction; material geometric / plastic deformation, and reliability modelling of physical systems) (Cerrone et al. 2014; Schroeder et al. 2016; Fourgeau et al. 2016; Yang, Zhang, and Liu 2013; Bazilevs et al. 2015);
2. system lifecycle mirroring, supporting decision-making in different ways: i) predicting the system's performances / behaviour in the long term (Bielefeldt, Hochhalter, and Hartl 2015; Grieves and Vickers 2016; Fourgeau et al. 2016), ii) granting data digital continuity along the lifecycle phases of the system (Abramovici, Gobel, and Dang 2016; Rosen et al. 2015), iii) checking the feasibility and optimizing the control software of the system (Schluse and Rossmann 2016), iv) simulating the orchestration of IoT devices (Canedo 2016).
3. statistically-based decision making and optimization (Kraft 2016), such as optimizing the system's behaviour / performances, by simulating it during the design phase (Gabor et al. 2016; Ríos et al. 2016; Arisoy et al. 2017; Abramovici, Gobel, and Dang 2016; Bajaj, Zwemer, and Cole 2016) or during other lifecycle phases, knowing its past and present states (Ríos et al. 2015; Smarslok, Culler, and Mahadevan 2012).

It is evident that DT modelling is full of promises in regard to the lifecycle management of assets. Hence, it can be assumed as a relevant mean to explicitly answer the related decision support needs.

3. RATIONALE AND OBJECTIVE OF THE STUDY

This research intends to contribute to a better understanding of the benefits that DTs can bring when they are applied in asset lifecycle management. Therefore, the state of the art analysis is just an initial step to provide the foundation of the study in regard to the needs generated by AM, as well as to the benefits to satisfy such needs, based on the DT concept. Field experience is also considered to complement the state of the art with hands on experience: some selected projects, experienced by the authors, are discussed to point out some use cases of DTs. It serves to explore the use of DT concept for asset-related decision-making.

The rationale behind the investigation can be motivated in terms of a technology transfer purpose. On one hand, there is the research that develops the Key Enabling Technologies (KETs such as the cited IoT, Big Data, advanced simulation and others), making them available for the industrial needs. On the other hand, there are the applications to solve practical problems within the industrial scope, in business processes and disciplines, in the case of this research the scope is AM. To enable the technology transfer. the research then aims at investigating how the DT functionalities and characteristics – available through various KETs – may be interconnected with the AM decision-making process. The final objective is to link the research areas of DT modelling and AM, in order to facilitate the use of new technologies and methodologies developed at KET level in the industrial AM setting. The selected projects can be considered as a manifestation of such a link.

4. INDUSTRIAL USE CASES ANALYSIS

Explorative application use cases analysis is provided to facilitate understanding the functionalities and characteristics of DTs to support AM. The use cases, related to different research projects in which the authors participated, are mapped in the AM framework represented in Fig. 2. The framework (Roda and Macchi 2016) is, in fact, used to organize different kinds of decision according to the asset lifecycle stages (Beginning of Life (BOL), Middle of Life (MOL) and End of Life (EOL)) and the asset control levels (Strategic, Tactical and Operational levels).

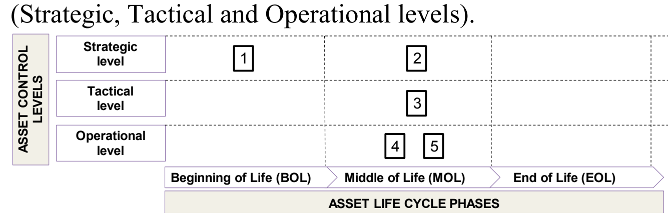

Figure 1 - Mapping the use cases in the AM framework (the numbers on the map refer to the different use cases)

Five cases have been chosen and few details are given hereafter for each of them, highlighting how the asset-related decision-making process can be supported by DT modeling. The cases are identified with numbers in accordance with the map provided by figure 2.

1. Asset configuration – The DT is used for modelling and simulating a production line, to evaluate its systemic Reliability, Availability, Maintainability performance (RAM performance), to finally predict its Total Cost of Ownership (TCO). It allows to assess the choice of the best design solution for the production line.
2. Asset reconfiguration – Similarly to the first use case, the DT is used for modelling and simulating a complex process production plant, to evaluate its systemic RAM performance, to finally predict its TCO. It allows to assess the choice of the best reconfiguration alternative to increase the availability of the plant.
3. Asset reconfiguration and planning – The DT is used as semantic data model within a web service-based control system for manufacturing systems. It forms the ground for an open, knowledge-driven Manufacturing Execution

System architecture, which allows quick reconfigurations of the system.

4. Asset commissioning – The DT is used as semantic data model, data analytics and advanced simulation, to make the virtual commissioning of the manufacturing system. Simulation of the system is based on a semantic data model and of a software structure that is able to analyse data in runtime. It allows a quick time to commission the system.
5. Asset condition monitoring and health assessment – The DT is used for the asset diagnosis, helping to assess its health status based on the monitored condition. The DT provides the data analytics in order to extract the features required for the diagnosis. It allows to limit unreliability situations.

The use cases put in evidence the wide variety of decisions supported by DTs in different asset lifecycle phases and at different asset control levels in a company. As better detailed hereafter, the use of DTs resulted to be consistent with the benefits generally discussed by literature. In this regard, two use cases are presented with further information, to discuss the functionalities of DTs used to support the asset-related decision-making.

Case 1. This case was developed within a process production plant of a company operating in the food sector. The primary challenge identified with the company was a decision support for design activities at the BOL of a Greenfield plant. A secondary challenge was also identified considering the potentiality to further use such a support for the activities in the MOL phase of the asset. In front of such challenges, the realization and use of the DT of the industrial plant was required, especially ground on the principles of risk orientation and system orientation. To this end, historical data, collected from similar existent plants working in similar operating conditions, as well as maintenance information provided by the OEMs were used to create a data model. Stochastic simulation was then adopted, integrating risk orientation, and run based on the reliability model of the plant (established through the Reliability Block Diagram technique) integrating system orientation, i.e. to enable to evaluate the impact of the interactions among the components of the system. The model enabled, firstly, the assessment of the design alternative solutions considered for the plant and, secondly, a proper evaluation of the TCO, through a model built on the performances achieved by the whole plant as an asset system (Roda, Garetti 2015). The functionalities of the DT of the plant were essential to support the asset-related decision-making, coping with the primary challenge through a statistically-based decision making that uses the simulation of the system's behaviour / performances. The secondary challenge is addressed by the possibility to use/re-use the system model of the plant, inherited from design to operation in order to obtain a system lifecycle mirroring, to finally allow predicting RAM performances and long-term behavior of the system based on the progressive state reached by the system along the MOL phase. Specifically to this end, not only historical data, but also actually recorded data and sensor data would be integrated to achieve the full functionality. During such extension, the life cycle orientation will be also enhanced, by incorporating additional long-term performances in order to drive decision-making during the MOL.

Case 5. The case study was developed within a process production plant of a company operating in the steel-making sector (Fumagalli et al., 2016). The primary challenge was the need for a decision support to manage maintenance activities in the MOL phase of a critical asset. In front of such challenge, the realization and use of the DT of the asset was required, especially ground on the principles of risk-orientation given the safety problem in steel-making industry and asset-centric orientation.

To this end, sensor data were modelled and analyzed through advanced analytics in order to extract the features required for the diagnosis of the health status of the asset. In particular, a condition monitoring tool was deployed by seeking the opportunities provided by plant automation.

The functionalities of the DT of the plant were essential to support the asset-related decision-making, coping with the primary challenge, by supporting improved statistically-based maintenance decision making at operational level, enabling to detect incipient failures through monitoring of the asset; thus, enhancing the operations by avoiding downtimes that may lead to risky consequences on people safety.

6. CONCLUSIONS

Digitization is a transformation process that leads to plenty of opportunities. It is enabling to introduce new KETs in various engineering and management applications. Considering AM as specific application, through use cases derived by research projects, it was possible to show that there is a convergence between the decision support needs of AM and the benefits provided by the functionalities of DTs along a system / asset lifecycle.

In particular, the use cases put in evidence the wide variety of decisions supported by DTs in different asset lifecycle phases and at different asset control levels in a company. Therein, the use of DTs is consistent with the benefits generally discussed by literature (section 2): i) system lifecycle mirror, by predicting performances and long term behaviour of the system (use case 1, 2) and by granting data digital continuity along the different lifecycle phases of the system (use case 3, 4); ii) improved maintenance decision making (use case 5).

The main evidence that emerges is that DTs can be considered a concept with high potential for asset lifecycle management. Next research will be relevant to classify KETs needed for DT modelling, with specific emphasis to AM as application domain. Besides, new methodological approaches to engineer DTs for asset-related decision-making will be required for the development of new tools / systems for decision support. Last but not least, DTs are expected to enrich the existent asset information system, thus enhancing the informed decision-making in AM.

ACKNOWLEDGMENT

This work was supported by the European Union's Horizon 2020 research and innovation programme under Grant No 678556, project *"MAYA", "MultidisciplinArY integrated simulAtion and forecasting tools, empowered by digital* *continuity and continuous real world synchronization, towards reduced time to production and optimization"*; and the ARTEMIS/ECSEL, Grant No. 332946, project eScop, "*Embedded systems Service-based Control for Open manufacturing and Process automation"*. Also, relevant contributions are from industrial projects funded by private companies.

REFERENCES

Abramovici, Michael, Jens Christian Gobel, and Hoang Bao Dang. 2016. "Semantic Data Management for the Development and Continuous Reconfiguration of Smart Products and Systems." CIRP Annals - Manufacturing Technology 65: 185–88.

Amadi-Echendu, Joe E., Kerry Brown, Roger Willett, and Joseph Mathew. 2010. Definitions , Concepts and Scope of Engineering Asset Management. Springer.

Arisoy, Erhan Batuhan, Guannan Ren, Erva Ulu, Nurcan Gecer Ulu, and Suraj Musuvathy. 2017. "A Data - Driven Approach to Predict Hand Positions for Two - Hand Grasps of Industrial Objects." In ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 11 pp.

Ashton, Kevin. 2009. "That ' Internet of Things ' Thing." RFiD Journal 22 (7): 97–114.

Atzori, Luigi, Antonio Iera, and Giacomo Morabito. 2010. "The Internet of Things : A Survey." Computer Networks 54 (15). Elsevier B.V.: 2787–2805.

Bajaj, Manas, Dirk Zwemer, and Bjorn Cole. 2016. "Architecture to Geometry – Integrating System Models with." In AIAA SPACE Forum, 1–19.

Bazilevs, Y., X. Deng, A. Korobenko, F. Lanza di Scalea, M.D. Todd, and S.G. Taylor. 2015. "Isogeometric Fatigue Damage Prediction in Large-Scale Composite Structures Driven by Dynamic Sensor Data." Journal of Applied Mechanics 82 (9): 1–12.

Bielefeldt, Brent, Jacob Hochhalter, and Darren Hartl. 2015. "Computationally Efficient Analysis of SMA Sensory Particles Embedded in Complex Aerostructures Using a Substructure Approach." In ASME Proceedings - Mechanics and Behavior of Active Materials.

Borek, Alexander, Ajith Kumar Parlikad, Philip Woodall, and Maurizio Tomasella. 2014. "A Risk Based Model for Quantifying the Impact of Information Quality." Computers in Industry 65 (2): 354–66.

Borgo, Stefano. 2014. "An Ontological Approach for Reliable Data Integration in the Industrial Domain." Computers in Industry 65 (9). Elsevier B.V.: 1242–52.

Canedo, Arquimedes. 2016. "Industrial IoT Lifecycle via Digital Twins." Proceedings of the Eleventh IEEE/ACM/IFIP International Conference on Hardware/Software Codesign and System Synthesis, 29.

Cerrone, A., Hochhalter J., Heber G., and Ingraffea A.. 2014. "On the Effects of Modeling As-Manufactured Geometry : Toward Digital Twin." International Journal of Aerospace Engineering 2014: 1–10.

CSN EN 16646. 2014. "Maintenance within Physical Asset Management." European Standard. European Standard.

Davis, Jim, Thomas Edgar, James Porter, John Bernaden, and Michael Sarli. 2012. "Smart Manufacturing , Manufacturing Intelligence and Demand-Dynamic Performance." Computers and Chemical Engineering 47. Elsevier Ltd: 145–56.

El-Akruti, Khaled, Richard Dwight, and Tieling Zhang. 2013. "The Strategic Role of Engineering Asset Management." International Journal of Production Economics 146 (1).

Fourgeau, E, E. Gomez, H. Adli, C. Fernandes, and M. Hagege. 2016. "System Engineering Workbench for Multi - Views Systems Methodology with 3DEXPERIENCE Platform. The Aircraft RADAR Use Case." Complex Systems Design & Management Asia 426: 269–70. doi:10.1007/978.

Fumagalli, L., Pala S., Garetti M., and Negri E. 2014. "Ontology-Based Modeling of Manufacturing and Logistics Systems for a New MES Architecture." In APMS 2014, IFIP Advances in Information and Communication Technology 438 (PART I), 192–200.

Fumagalli, L., Macchi, M., Colace, C., Rondi, M. and Alfieri, A., 2016. "A Smart Maintenance tool for a safe Electric Arc Furnace". IFAC-PapersOnLine, 49(31), pp.19-24.

Gabor, Thomas, Lenz Belzner, Marie Kiermeier, Michael Till Beck, and Alexander Neitz. 2016. "A Simulation-Based Architecture for Smart Cyber-Physical Systems." In Autonomic Computing (ICAC), 2016 IEEE International Conference on, 374–79.

Garetti, M., Fumagalli L., and Negri E.. 2015. "Role of Ontologies for CPS Implementation in Manufacturing." MPER - Management and Production Engineering Review 6 (4): 26–32.

Grieves, Micheal, and John Vickers. 2016. "Digital Twin : Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems." In Transdisciplinary Perspectives on Complex Systems, 85–113.

Gruber, TR. 1995. "Toward Principles for the Design of Ontologies Used for Knowledge Sharing." International Journal of Human-Computer Studies 43: 907–28.

Hastings, Nicholas A. J. 2010. Physical Asset Management. Media. doi:10.1007/978-1-84882-751-6.

Heymans, Stijn, Li Ma, Darko Anicic, Zhilei Ma, Nathalie Steinmetz, Yue Pan, Jing Mei, et al. 2008. "ONTOLOGY REASONING WITH LARGE DATA REPOSITORY." In Ontology Management, 89–128. Springer US.

ISO 55000:2014(E). 2014. "Asset Management — Overview, Principles and Terminology."

Kans, Mirka, and Anders Ingwald. 2008. "Common Database for Cost-Effective Improvement of Maintenance Performance." International Journal of Production Economics 113: 734–47.

Komonen, K, H. Kortelainen, and M Räikkonen. 2006. "An Asset Management Framework to Improve Longer Term Returns on Investments in the Capital Intensive Industries." In Engineering Asset Management, Springer London, 418–32.

Koronios, Andy, Shien Lin, and Jing Gao. 2006. "A Data Quality Model for Asset Management in Engineering Organisations." International Conference on Information Quality (MIT IQ Conference), 25.

Kraft, Edward M. 2016. "The US Air Force Digital Thread / Digital Twin – Life Cycle Integration and Use of Computational and Experimental Knowledge II . The Evolution of Integrated Computational / Experimental Fluid Dynamics." In 54th AIAA Aerospace Sciences Meeting, 1–22. doi:10.2514/6.2016-0897.

Lee, Jay, Hung-an Kao, and Shanhu Yang. 2014. "Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment." In Procedia CIRP, 16:3–8. Elsevier B.V. doi:10.1016/j.procir.2014.02.001.

Negri, E., L. Fumagalli, M. Garetti, and L. Tanca. 2016. "Requirements and Languages for the Semantic Representation of Manufacturing Systems." Computers in Industry 81. Elsevier B.V.: 55–66.

Negri, E., L. Fumagalli, and M. Macchi. 2017. "A Review of the Roles of Digital Twin in CPS-Based Production Systems." Procedia Manufacturing 11 (June). The Author(s): 939–48.

Ouertani, M. Z., Ajith K. Parlikad, and Duncan McFarlane. 2008. "Asset Information Management: Research Challenges" II International Conference on Research Challenges in Information Science. IEEE, 361–70.

Ríos, José, Juan Carlos Hernandez, Manuel Oliva, and Fernando Mas. 2015. "Product Avatar as Digital Counterpart of a Physical Individual Product : Literature Review and Implications in an Aircraft." In ISPE CE

Ríos, José, Fernando Mas Morate, Manuel Oliva, and Juan Carlos Hernández. 2016. "Framework to Support the Aircraft Digital Counterpart Concept with an Industrial Design View." International Journal of Agile Systsems and Management 9 (3): 212–31.

Roda, I, and M. Macchi. 2016. "Studying the Funding Principles for Integrating Asset Management in Operations: An Empirical Research in Production Companies." IFAC-PapersOnLine 49 (28). Elsevier B.V.

Roda, I., and Garetti M.. "Application of a Performance-driven Total Cost of Ownership (TCO) Evaluation Model for Physical Asset Management." In 9th WCEAM Research Papers, pp. 11-23. Springer International Publishing, 2015.

Rosen, Roland, Georg Von Wichert, George Lo, and Kurt D Bettenhausen. 2015. "About The Importance of Autonomy and Digital Twins for the Future of Manufacturing." In IFAC-PapersOnLine, 48:567–72. Elsevier Ltd. doi:10.1016/j.ifacol.2015.06.141.

Sarma, Sanjay, David L Brock, and Kevin Ashton. 2000. The Networked Physical World. Auto-ID Center White Paper MIT-AUTOID-WH-001.

Schluse, M., and Rossmann J.. 2016. "From Simulation to Experimentable Digital Twins." In Systems Engineering (ISSE), IEEE International Symposium on, 1–6.

Schroeder, Greyce N., Charles Steinmetz, Carlos E. Pereira, and Espindola Danubia B. 2016. "Digital Twin Data Modeling with AutomationML and a Communication Methodology for Data Exchange." In IFAC-PapersOnLine, 49:12–17. Elsevier B.V.

Schuman, Charles a., and Alan C. Brent. 2005. "Asset Life Cycle Management: Towards Improving Physical Asset Performance in the Process Industry." International Journal of Operations & Production Management 25 (6): 566–79.

Shafto, Mike, Mike Conroy, Rich Doyle, Ed Glaessgen, Chris Kemp, Jacqueline LeMoigne, and Lui Wang. 2010. "DRAFT Modeling, Simulation, Information Technology & Processing Roadmap. Technology Area 11."

Smarslok, Benjamin P, Adam J Culler, and Sankaran Mahadevan. 2012. "Error Quantification and Confidence Assessment of Aerothermal Model Predictions for Hypersonic Aircraft." In 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, 1817.

Wang, Hai-Kun, R. Haynes, Hong-Zhong Huang, Leiting Dong, and Satya N. Atluri. 2015. "The Use of High-Performance Fatigue Mechanics and the Extended Kalman / Particle Filters , for Diagnostics and Prognostics of Aircraft Structures." CMES: Computer Modeling in Engineering & Sciences 105 (1): 1–24.

Weyer, Stephan, Torben Meyer, Moritz Ohmer, and Dominic Gorecky. 2016. "Future Modeling and Simulation of CPS-Based Factories : Future Factories : Future Factories : Example from the Automotive Industry Future and Factories : An Example from the Automotive Example from the Automotive an Example from the Automotive Industry." In IFAC PapersOnLine, 49:97–102. Elsevier

Yang, Jian, Wei Zhang, and Yongming Liu. 2013. "Subcycle Fatigue Crack Growth Mechanism Investigation for Aluminum Alloys and Steel (Special Session on the Digital Twin)." In 54th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, 1499.