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Digitalisation in Operations to Support the Engineering Asset Management

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Abstract The aim of this project is to explore potential benefits that digitalization could provide when it enhances the links between the Cyber-Physical Systems describing the asset and the operations involving such as- set. Production and maintenance activities are included in the Operations functional area for this work. To obtain the expected benefits, the participation of relevant variables must be established according to a convenient ontology. Other activities such as model building and damage law inference are also required. A high level framework to connect all the needed activities are de- rived and links are discussed. Finally, some managerial considerations are also presented.

Index Terms - Digitalization, Industry 4.0, Asset man- agement, CPS, IoT, IoS

INTRODUCTION

Asset management (AM) has gained popularity in recent years. Definitions of asset management tend to be broad in scope and cover a wide variety of areas, including general management, operations, and production arenas, and financial and human capital aspects. Although the broader conceptualization allows for a multifaceted investigation of physical assets, the arenas constitute a multiplicity of spheres of activity. Here, the term engineering asset management is under- stood as the total management of physical, as opposed to financial, assets. However, engineering assets have a financial dimension that reflects their economic value and the management of this value is an important part of overall engineering asset management. The conceptualization of asset management enables it to be an interdisciplinary field of endeavor, and we include concepts from management, business, and engineering. The framework is also broad, emphasizing the life cycle of the asset [1].

The management of assets in complex because it frequently involves multi-unit systems with an empha- sis on two multi-asset categories: systems of homoge- neous assets and systems of heterogeneous assets. As asset systems become more complicated, researchers have used different terms to refer to their specific problems, as can be seen in [2, 3]. The bulk of costs in assets can be found in costs for maintenance and capital depreciation. Therefore, a comprehensive ap- proach to asset management focuses on the ’lifecycle costs’ of the individual equipment. The objective of the life management process is the optimal utilization of the remaining life time with respect to a given reliability of service and a constant distribution of costs for reinvestment and maintenance that ensures a suitable return [4].

When people think in terms of asset management, it is about changing the approach from reactive to proactive. Proactive asset management allows for:

- Reduced failure-related repair or replacement costs,
- Reduced inspection and maintenance costs,
- Reduced asset lifetime cost,
- Increased asset reliability and availability.

There is little doubt that companies are increas- ingly leveraging digital technologies to improve their bottom line through Industry 4.0. Industry 4.0 is a collective term for technologies and concepts of value chain organization. Within the modular structured Smart Factories of Industry 4.0, Cyber-Physical Systems (CPS) monitor physical processes, create a virtual copy of the physical world, and make decentral- ized decisions. Through the Internet of Things (IoT), CPSs communicate and cooperate with each other and humans in real time. Through IoS (Internet of Services), participants in the value chain offer and use internal and cross-organizational services [5].

According to the definition of Industry 4.0, four fundamental technologies can be recognized:

- Smart Factories (SFs),
- Cyber-physical systems (CPS),
- The Internet of Things (IoT), and
- The Internet of Service (IoS).

Researchers in manufacturing mainly adopt a technology-centered approach for CPS, favoring in priority the definition and allocation of tasks to au- tomated intelligent systems while considering at the same time that humans, being operators or supervisors, will be there only to handle any unexpected situa- tions. A CPS is a type of scheme that monitors the physical systems while creating a virtual copy and developing decisions in a decentralized way. Within the CPS, the control elements and sensors of the system are connected to machines and devices, along with installations, networks, and vessels, where the IoT is widely used for such communications. When decentralization is emphasized, cloud computing plays a vital role in the upcoming Internet of Services, while allowing provision of on-demand requests, computa- tional infrastructures, and platforms. The IoS protocol offers a variety of internal factory services horizontally throughout the value chain [6]. However, most of the time, the design of an industrial CPS focuses mainly on providing information to human operators during their process control activities [7]. Furthermore, human aspects are often taken into account only at the end of the design process, that is, once the control system has been designed.

Although it happens in all industries, such ef- fects are highlighted in complex industries such as the chemical or steel industries, where heterogeneous systems are regularly involved in production assets.

However, it also happens in other less technologically advanced sectors, such as the construction industry or the service sectors. A good example of this is Build- ing Information Modeling(BIM), which implies the use of virtual building information models to develop building design solutions and design documentation, but also to analyze construction processes. Recent ad- vances in IT have enabled advanced knowledge man- agement, which in turn facilitates sustainability and improves asset management in the civil construction industry according to [8].

However, much little attention has been paid to in- creasing asset reliability and availability, based on the operational information available and the estimation of pending actions, including their different setups, which can involve different affectation levels for the assets. Such integrative perspective means, just for instance in the previous case of BIM, it will imply to extend the coverage from the construction process to the usage of the infrastructure, by monitoring the asset condition and integrating the information coming from the existing maintenance policies.

Future climate change will also result in the ac- celerated aging of active equipment exposed to the environment. Furthermore, climate change increases the risk and occurrence of climatic events that impact network reliability. All of these factors highlight the value of the integrative perspective of technical asset management. Therefore, this article will discuss ways to combine Industry 4.0 aspects with asset management to increase value creation. Section State of the Artwill introduce specific initiatives that are worth considering. Section Framework will introduce the main context and framework to be considered, while Section Discussion and Conclusions will deal with the main outcomes of this ongoing work.

STATE OF THE ART

There are quite significant reviews in the literature focused on AM, such as [9, 10, 11, 12, 13] have been conducted in recent years. In such analyses different techniques such as connecting words coming from the Natural Language processing techniques of the published papers were carried out. Significant con- nections of AM towards related concepts have been identified such as "strategy", "management", "failure", "risk", "practice", "probability", "condition monitor- ing", "change", "performance" among others.

On the other hand, there are new opportunities coming from new added value services based on the widespread use of connected IoT devices that bring a significant amount of data to clouds, being processed with advanced techniques based on artificial intelli- gence as presented in [14, 15].

Although the integration of services and IoT de- vices is complex by definition due to protocol diversity, time alignment, item sequencing, and noisy environ- ments. Such complexity levels are emphasized due to the contribution of heterogeneous environments [15]. The most popular option to deal with these situations is to use semantic standards and related technologies to deal with interoperability issues [16, 17, 18].

Simulations are used in various stages of the life cycle by different engineering disciplines, by different kinds of end user in different infrastructures combining different simulation domains and engineering meth- ods in a variety of different application areas. Today, most simulation applications solve a single specific application, in a single context. Changing only one aspect, such as exchanging from a dedicated simulation context to a virtual one, often results in complicated data exchange processes (and loss of data) or even requires the establishment of an entire new simulation application [19]. Frequently, simulations need to be configured according to parameters obtained through IoT sensors and communication protocols. Simulations aim to describe estimated expected behaviors of the digital twin.

Although most digital twins focus on building the CPS of the interesting system by describing its opera- tion, some researchers are pushing to expand the field, enabling the adoption of building information mod- eling (BIM) for asset management within the archi- tecture, engineering, and construction sectors. In fact, BIM-enabled asset management during the operation and maintenance phase has been increasingly attracting increasing attention both in research and practice [20]. The use of a Hybrid Digital Twin approach by de- scribing an application example of the maintenance of spiral welded steel industrial machinery has been reported in **(author?)** [21], with a focus on the sup- port of the digital twin for predictive maintenance. The authors also propose to support cognitive digital twins, providing support for learning, understanding and planning, including also the use of domain and human knowledge [22].

From the bibliographic analysis carried out, it is
clear that more work is needed to integrate CPS includ- ing IoT and IoS with Operations and Maintenance, but also with Engineering Asset Management, where spe- cific frameworks need to be further elaborated, because there are just a few seminal discussions regarding all concepts, such as [20, 23].

FRAMEWORK

Looking to establish a consistent framework be- tween all relevant entities, let us design an interesting system by Si that can be an asset or component of it. The hierarchical model of asset is presented in Fig. 1, where its lower level is devoted to the minimal inter- esting subsystem of interest from a functional point of view. An interconnected group of such subsystems built a specific asset, such as manufacturing equipment, etc., placed at level two of the figure. Asset sequences are generally involved in the development of products through processes. We have represented at level three an individual value stream (VS), to retain the Lean Manufacturing notation. Finally, but yet importantly, the upper level represented is the facility as a whole, which involves different VS(s), each of them defined based on the participation of one or more assets, raw materials, different types of workers, etc. It is relevant to highlight that the adopted perspective is endless at both ends. At the lower level, the subsystem can have single elements with part numbers that are relevant at the maintenance level, but not at the functional level. On the other hand, a group of factories can be linked, allowing the integration of different parts of the product through the supply chain. On that layer, it is possible to include distribution channels and markets. However, only the layers included in Fig. 1 are enough for the purpose of this analysis. The operation of the asset (or its components) means a natural degradation of its performance due to its usage (di), while maintenance operations perform (partial) recovery of damage (si), and it is presented in Fig. 2. Of course, specific laws describing damage evolution can have different expressions depending on factors such as process operational conditions, raw material quality, variable(s) describing the damage, etc.

In any case, the selection of operating conditions for individual items or orders can have an im- pact on the operating time (opi) per cycle of opera- tion/maintenance. Maintenance requires stopping the asset for a period of time (ri) and using resources and elements to repair/replace elements.

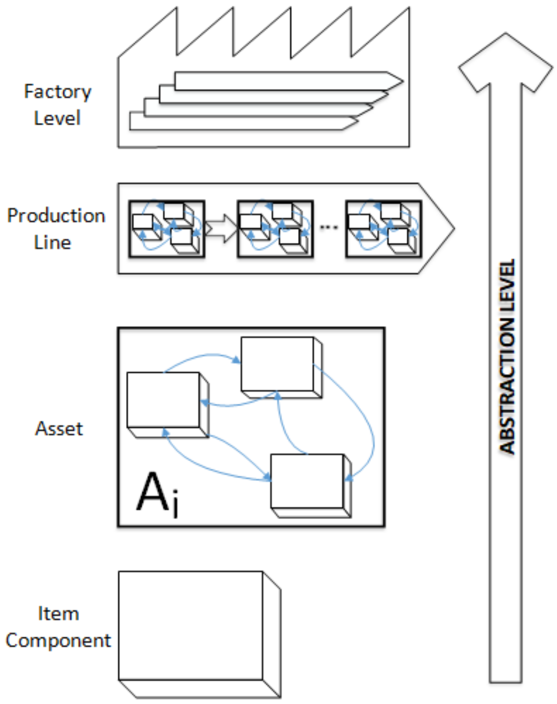

Figure 1.
Hierarchical concept of asset embedding.

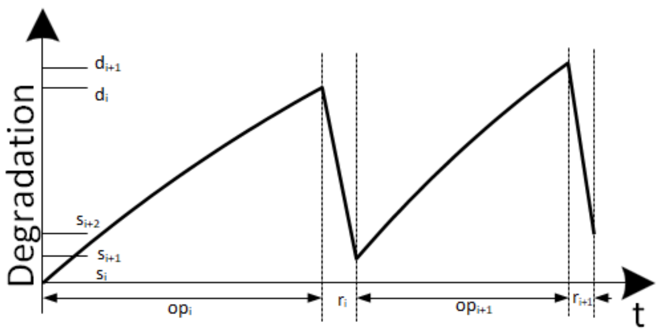

Figure 2.
System evolution of damage because of its usage.

Figures represent the interrelationship between op- erations, maintenance, and impact on assets, although such relationships are described by different elements and physical variables. All these components can be represented properly by a convenient ontology struc- ture. Obviously, required physical variables are not just restricted to those related to damage description, but

they need to include variables related to asset usage (energy through time, speed, operating temperature, etc.), to the product, to the workers, etc. Data from these variables are collected through the Internet of Things (IoT), and the interaction of the asset with other systems or services is handled by the IoS. To be realistic in the context representation of the asset, redundancy in signals is convenient to avoid synchro- nization issues and to increase the signal-to-noise ratio. Once the relationship between all fields has been established, let us understand how digital twins and digital-based maintenance can provide additional value in the reference context. If the digital twin represents the asset well, it can be used not only to identify specific biases between the measured parameters in real time and those predicted by the digital twin, but also to forecast future status and performance when specific operating parameters are considered through a what if analysis [24]. The forecast analysis will most probably require AI-based models, which will require an extensive usage of the historical data collected from the system behavior, which again will require IoT and IoS support, and or good knowledge of the physical models involved if hybrid AI models are adopted.

Another critical aspect is to understand the importance of maintenance in the complete picture.

Nowadays, the European industry has to deal with global markets and strong competition from other re- gions where costs are much lower. Therefore, it be- comes extremely relevant to increase trust in product and service. Maintenance operations have a significant influence on company costs (10%-40% depending on the size of the company and the branch of the industry). This makes necessary an innovative maintenance ap- proach with a novel design, reliability-based, in which the industrial system is considered as a whole. Pre- dictive maintenance, sometimes called "online moni- toring," "condition-based maintenance", or "risk-based maintenance", has a long history. From visual inspec- tion, which is the oldest method, yet still one of the most powerful and widely used predictive main- tenance methods, automated methods have evolved to use advanced signal processing techniques based on pattern recognition, including neural networks, fuzzy logic, and empirical and physical modeling driven by data [25]. These techniques can be divided into several categories. The first category uses signals from existing process sensors to help verify the performance of the sensors and process-to-sensor interfaces, and also to identify problems in the process.

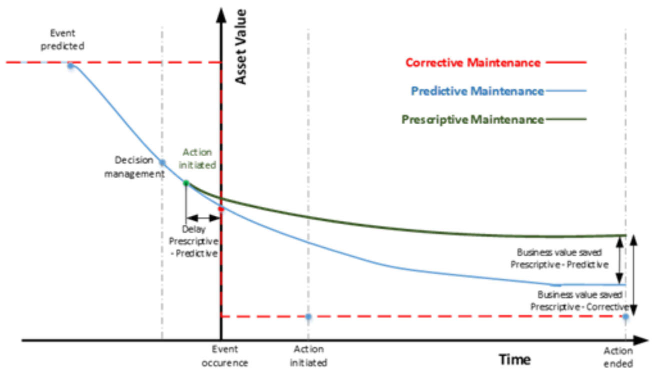

Figure 3.
Differences regarding the business value of assets.

Another category depends on signals from addi- tional sensors that are installed on plant equipment. The variables read from these sensors are then trended to identify the onset of degradation or failure. With each additional parameter that can be measured and correlated with the condition of the equipment, the diagnostic capabilities of the category can increase exponentially [25]. Classic maintenance practices (cor- rective or preventive) must be replaced by the most reliable techniques based on preventive methods. For this purpose, the most innovative maintenance strategy is prescriptive maintenance.

The innovative idea of connecting asset damage forecasts with operational decisions is a challenge that will require the development of advanced tools and methodologies that are applicable but also capable of generalization to any industry. Another challenge comes from the fact that maintenance and produc- tion departments are normally independent of each other [26]. It is a challenge to change such structures, especially because decision makers are also unfamiliar with the consideration of damage propagation influencing the scheduled production of orders. To get the full benefits of the integrative view of prescriptive maintenance, both actions (organizational structures and changes in decision making) are necessary [27].

Normally, the proposed use of prescriptive analyt- ics in an innovative way to ensure optimal asset estimation of availability; by overlaying production schedule commitments on asset maintenance requirements (see Fig. 3. Analytical tools and methodologies are required not only to predict what is likely to occur, but also to offer a 'what if' analysis of alternatives to provide the

optimal forecast scenario that can alter the outcome. It will provide the tools to integrate maintenance and production activities scheduling in order to maximize the life of production assets and minimize total costs (including loss-of-production cost, maintenance cost, and all associated costs). Managers will be able to prioritize maintenance and production activities, make replacement vs. repair decisions, and define appropriate timing. This makes a maintenance approach with novel design and reliability-based, and considering the industrial system as a whole necessary. Due to the holistic concept, it is expected that the efficiency of the in-service increases between 12% and 18% due to the integrated view of the damage of the units developed, which helps not only identify events, but also monitor business value against operation. This solution will help schedule the proper actions to increase efficiency. Potentially better solutions can be offered to decision managers. Finally, due to the systematic approach, the pressure for early termination can be removed from maintenance people, which will impact the accident rate pushing for its reduction. Finally, from the managerial perspective, such an integrated concept will support increased transparency. It also provides managers with an actual view of the business value of units and the facility as a whole. This dimension is unneglectable, as it greatly contributes to better root decisions by understanding different levels of impact in different areas of the business.

Current systems and maintenance strategies may not necessarily be able to detect all types of deterio- ration and faults. One reason for this is a lack of high frequency data, which contains enough information to be able to detect machine degradation far enough in advance as to allow remedial actions to be planned effectively. At present, most production systems are monitored by supervisory control and data acquisition (SCADA) systems, which provide data only on several minute averages, whereas standard machinery diagnos- tics practices require high frequency vibration moni- toring among other high frequency signals. Therefore, it is clear that the concepts of designing the system matter. Being aware of the relevance from the earliest steps of the system design, this proposal looks to consider operational parameters within wide range of sampling frequencies up to 2kHz, including advanced compression techniques like wavelets or FFT. Indeed, variety of input sources are considered (signal values like pressure, sound level, etc., images like thermo-

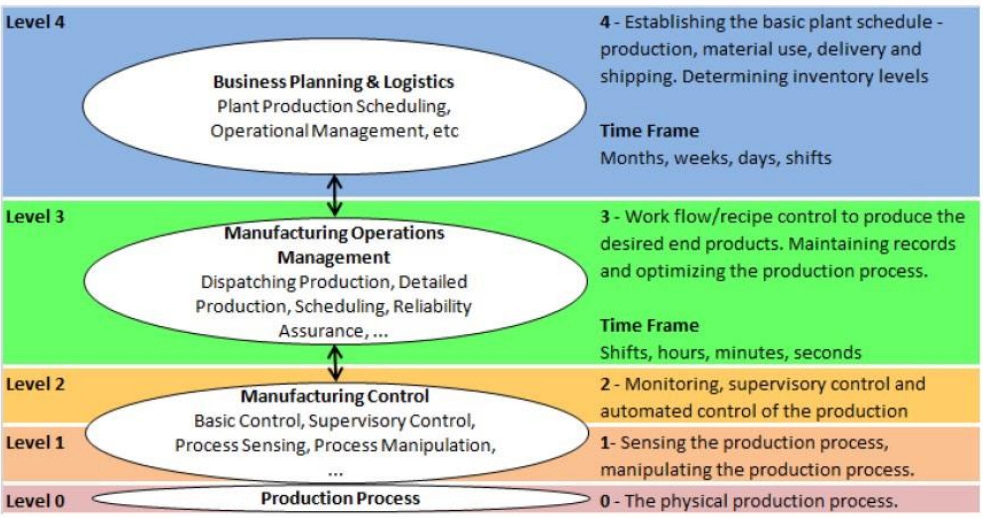

Figure 4.
Defined ISA95 levels and interpretive placement of different activities.

graphic pictures, etc., numeric vectors like the three axes vibration, etc.). Another relevant aspect is that in order to look for failure causes, traditional approaches are focused on considering human-oriented feature selection and related criteria. Although it is meaningful, this proposal looks to implement self-learning features capabilities by using deep learning technologies [28] as well as soft sensors [29]. Cognitive systems engineering techniques provide an opportunity to even utilize a dynamic resource, people acting as soft sensors. The literature is extensive on techniques for combining data from electronic sensors [30] but little work exists on combining data from humans with those from elec- tronic sensors [31], which is another key concept in this proposal.

To reduce false alarms, two layers of analysis can be considered for working together. The first one is locally focused, and it is based on both event- and accumulated damage models per subsystem or main component. The second looks at the reliability of the whole system and adopts state-space methods due to their flexibility and power in capturing dependence conditions in the system. In some specific sectors, such as the maintenance of services in buildings, the management of decision making can also be integrated through existing standards such as BIM, which will play the role of MES system (levels 3 and below, according to the ISA 95 standard) (see Fig. 4), while ERP runs at level 4 in the case of industrial production.

DISCUSSION AND CONCLUSIONS

Based on the current state of digitalization, sig- nificant benefits can be expected from the integration between operations, maintenance, and CPS with the support of IoT and IoS when asset management. How- ever, implementation according to different use cases can be promoted when a more generic framework is provided. After the discussions carried out in Section the dependencies of each technology and its business function become available. Therefore, Fig. 5 presents the relationship between different components as sug- gested by the analysis.

The promoted framework is generic and agnostic with respect to the different technologies that support implementations. Implementation will require a long journey ahead, as the characterization of damage functions requires deep analysis and variable selection. The required selection of variables, including redundancy, will need an appropriate ontology, not restricted to asset management. Such long-term work will only be possible when high-management teams are fully committed to supporting the significant effort required to transform the organization. In addition to the strong support of senior management, there are still signif- icant technical challenges at different stages in the process. Standards are convenient tools to help meet these challenges.

When implementing all components, reinforced learning can be considered to find the optimal answer to the required scenario to achieve demand and min- imize cumulative degradation for all assets involved. To keep solutions flexible enough, the cost function can be selected and the sensitivity analysis can be implemented in order to provide the decision manager with all the information.

Future work will focus on degradation laws and the impact of operational parameters on such laws, as a needed step in the process. In fact, the sensitiveness of maintenance activities to damage levels requires further research.

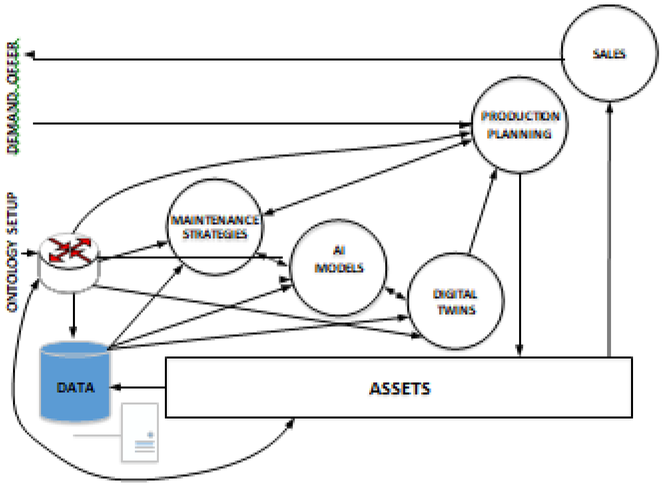

Figure 5.
System evolution of damage because of its usage.

REFERENCE

[1] J. E. Amadi-Echendu, R. Willett, K. Brown, T. Hope, J. Lee, J. Mathew, N. Vyas, and B.-S. Yang, "What is engineering asset management?" in *Definitions, concepts and scope of engineering asset management*. Springer, 2010, pp. 3–16.

[2] S. M. Davis *et al.*, "Brand asset management," *Driving profitable growth through your brands. San Francisco*, 2000.

[3] S. Petchrompo and A. K. Parlikad, "A review of asset management literature on multi-asset sys- tems," *Reliability Engineering & System Safety*, vol. 181, pp. 181–201, 2019.

[4] J.Schneider, A. J. Gaul, C. Neumann, J. Hogräfer, W. Wellßow, M. Schwan, and A. Schnettler, "Asset management techniques," *International Journal of Electrical Power & Energy Systems*, vol. 28, no. 9, pp. 643–654, 2006.

[5] M. Hermann, T. Pentek, and B. Otto, "Design principles for industrie 4.0 scenarios," in *2016 49th Hawaii international conference on system sciences (HICSS)*. IEEE, 2016, pp. 3928–3937.

[6] H. I. AL-Salman and M. H. Salih, "A review cyber of industry 4.0 (cyber- physical systems (CPS), the internet of things (IoT) and the internet of services (IoS)): Components, and security challenges." *Journal of Physics: Conference Series*, vol. 1424, no. 1, p. 012029, dec 2019. [On- line]. Available: https://doi.org/10.1088/1742- 6596/1424/1/012029

[7] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber- physical systems architecture for industry 4.0- based manufacturing systems," *Manufacturing letters*, vol. 3, pp. 18–23, 2015.

[8] R. A. Kivits and C. Furneaux, "Bim: enabling sustainability and asset management through knowledge management," *The Scientific World Journal*, vol. 2013, 2013.

[9] E. Gavrikova, I. Volkova, and Y. Burda, "Strate- gic aspects of asset management: An overview of current research," *Sustainability*, vol. 12, no. 15, p. 5955, 2020.

[10] L. F. Gay and S. K. Sinha, "Resilience of civil infrastructure systems: literature review for im- proved asset management," *International Journal of Critical Infrastructures*, vol. 9, no. 4, pp. 330– 350, 2013.

[11] C. B. H. Nel and J. Jooste, "A technologically- driven asset management approach to man- aging physical assets-a literature review and research agenda for'smart'asset management," *South African Journal of Industrial Engineering*, vol. 27, no. 4, pp. 50–65, 2016.

[12] P. F. Katina, J. C. Pyne, C. B. Keating, and D. Komljenovic, "Complex system governance as a framework for asset management," *Sustainabil- ity*, vol. 13, no. 15, p. 8502, 2021.

[13] A. Attwater, J. Wang, A. Parlikad, and P. Russel, "Measuring the performance of asset manage- ment systems," in *Asset Management Conference 2014*. IET, 2014, pp. 1–6.

[14] M. Grijalvo Martín, A. Pacios Álvarez, J. Ordieres-Meré, J. Villalba-Díez, and G. Morales-Alonso, "New business models from prescriptive maintenance strategies aligned with sustainable development goals," *Sustainability*, vol. 13, no. 1, 2021. [Online]. Available: https://www.mdpi.com/2071-1050/13/1/216

[15] S. Alberternst, A. Anisimov, A. Antakli, B. Duppe, H. Hoffmann, M. Meiser, M. Muaz, D. Spieldenner, and I. Zinnikus, “Orchestrating heterogeneous devices and ai services as virtual sensors for secure cloud-based iot applications,” *Sensors*, vol. 21, no. 22, p. 7509, 2021.

[16] H. Rahman and M. I. Hussain, “A comprehensive survey on semantic interoperability for internet of things: State-of-the-art and research challenges,” *Transactions on Emerging Telecommunications Technologies*, vol. 31, no. 12, p. e3902, 2020.

[17] S. Sun, X. Zheng, J. Villalba-Díez, and J. Ordieres-Meré, “Data handling in industry 4.0: Interoperability based on distributed ledger tech- nology,” *Sensors*, vol. 20, no. 11, p. 3046, 2020.

[18] X. Zheng, J. Lu, and D. Kiritsis, “The emergence of cognitive digital twin: vision, challenges and opportunities,” *International Journal of Produc- tion Research*, pp. 1–23, 2021.

[19] M. Schluse and J. Rossmann, “From simulation to experimentable digital twins: Simulation-based development and operation of complex technical systems,” in *2016 IEEE International Symposium on Systems Engineering (ISSE)*. IEEE, 2016, pp. 1–6.

[20] Q. Lu, X. Xie, A. K. Parlikad, J. M. Schooling, and E. Konstantinou, “Moving from building in- formation models to digital twins for operation and maintenance,” *Proceedings of the Institution of Civil Engineers-Smart Infrastructure and Con- struction*, vol. 174, no. 2, pp. 46–56, 2020.

[21] P. Unal, O. lbayrak, M. Jomâa, and A. J. Berre, *Data-Driven Artificial Intelligence and Predictive Analytics for the Maintenance of Industrial Machinery with Hybrid and Cognitive Digital Twins*. Cham: Springer International Publishing, 2022, pp. 299–319. [Online]. Available: https://doi.org/10.1007/978- 3-030-78307-5_14

[22] Ö. Albayrak and P. Ünal, “Smart steel pipe pro- duction plant via cognitive digital twins: A case study on digitalization of spiral welded pipe ma- chinery,” in *Cybersecurity workshop by European Steel Technology Platform*. Springer, 2020, pp. 132–143.

[23] M. Mirhosseini and F. Keynia, “Asset manage- ment and maintenance programming for power distribution systems: A review,” *IET Generation, Transmission & Distribution*, vol. 15, no. 16, pp. 2287–2297, 2021.

[24] D. Adamenko, S. Kunnen, R. Pluhnau, A. Loibl, and A. Nagarajah, “Review and comparison of the methods of designing the digital twin,” *Pro- cedia CIRP*, vol. 91, pp. 27–32, 2020.

[25] H. M. Hashemian, “State-of-the-art predictive maintenance techniques,” *IEEE Transactions on Instrumentation and measurement*, vol. 60, no. 1, pp. 226–236, 2010.

[26] F. Shrouf, B. Gong, and J. Ordieres-Meré, “Multi- level awareness of energy used in production processes,” *Journal of cleaner production*, vol. 142, pp. 2570–2585, 2017.

[27] F. Shrouf, J. Ordieres, and G. Miragliotta, “Smart factories in industry 4.0: A review of the concept and of energy management approached in pro- duction based on the internet of things paradigm,” in *2014 IEEE international conference on indus- trial engineering and engineering management*.IEEE, 2014, pp. 697–701.

[28] P. Tamilselvan and P. Wang, “Failure diagno- sis using deep belief learning based health state classification,” *Reliability Engineering & System Safety*, vol. 115, pp. 124–135, 2013.

[29] C. Shang, F. Yang, D. Huang, and W. Lyu, “Data- driven soft sensor development based on deep learning technique,” *Journal of Process Control*, vol. 24, no. 3, pp. 223–233, 2014.

[30] L. Gamage and C. De Silva, “A system frame- work with online monitoring and evaluation for design evolution of engineering systems,” *Journal of computing and information science in engi- neering*, vol. 10, no. 3, 2010.

[31] J. T. Bernardo, “A methodology for hard/soft information fusion in the condition monitoring of aircraft,” in *Multisensor, Multisource Information Fusion: Architectures, Algorithms, and Applica- tions 2013*, vol. 8756. SPIE, 2013, pp. 58–71.